Design and Optimization of Drone Assisted Wildfire Fighting System

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***Abstract*—The utilization of autonomous agents such as multiple UAVs has been continually increasing to recognize spot fires and screen out of control fire hazards moving toward a structure, fence, forest, or firefighting crew via remote sensing. Wildfires have caused catastrophic losses as their economic and regional impact were not reduced. The monitoring and suppression of wildfire with drones using the Voronoi Partitioning Algorithm is proposed in this report. Robot Operating System was used to deploy quadcopters in an area using Centroidal Voronoi Tessellation. By the algorithm, a plane with n foci is divided into convex polygons such that every polygon contains precisely one generating point. In Voronoi Partitioning, UAVs are situated in the centroid of the partitioned area hence the area covered by each drone is almost equal, and an unbiased search is followed through. The MATLAB simulation of the Voronoi algorithm was run with 'n' number of drones to see the configuration firsthand and see how every drone occupied an equal area density to carry out the specific application, making the detection process smoother and more efficient. Hector Quadrotor was simulated in Gazebo environment and related packages were configured to emulate it. Rviz was used to check the function of the cameras for fire detection and was run alongside the Hector Quadrotor. A strategy that could be used for forest firefighting by using multi drone systems is elaborated in this report. A literary review was done to discuss the various available path planning techniques and drone systems to detect fires. Using Voronoi-Tessellation in MATLAB, the path for the robots' search was developed. Separately, the drone used was simulated in a virtual environment called Gazebo. By using combinations of different drones and thermal cameras in the simulation, multiple alternatives have been recognized. Further, an addition of a thermal attribute to the environment to simulate a real-world scenario and systemize the communications between various instances of the drones were made to detect wildfire affected areas accurately.**

Keywords*—*Wildfire Detection; Thermal Imaging; UAV Coordination; Voronoi Partitioning; Multi-Drone Systems; ROS-Gazebo Simulation; Autonomous Aerial Surveillance; Wildfire Modeling.

I. INTRODUCTION

Wildfires represent one of the most destructive natural disasters globally, intensified by climate anomalies and increasingly dry landscapes. Rapid detection and real-time monitoring are essential to mitigate the ecological, economic, and human losses caused by these events. Unmanned aerial vehicles (UAVs) have emerged as a powerful tool in wildfire surveillance due to their ability to access remote areas, provide aerial situational awareness, and collect data in real-time without endangering human operators. However, the effectiveness of UAVs in operational wildfire scenarios is limited by several practical challenges, including short battery life, sensitivity to adverse weather conditions, and the risk of communication breakdowns in dense forest environments. To enhance the reliability and scalability of UAV-based systems, researchers have explored various area coverage and path planning algorithms. Among these, Ant Colony Optimization and Levy Flight offer stochastic and adaptive strategies but often suffer from high computational complexity or lack of spatial structure. Voronoi Tessellation, by contrast, provides a geometrically intuitive method to partition the search space into non-overlapping regions centered around each UAV, ensuring balanced coverage and minimizing redundancy. This approach is particularly suited for coordinated multi-drone operations in dynamic environments. In recent years, wildfire detection technologies have also advanced through the integration of deep learning frameworks, multi-modal sensor fusion (e.g., RGB and thermal cameras), and AI-enhanced navigation systems. Models such as YOLOv5, AF-Net, and FCLGYOLO have demonstrated high accuracy in fire segmentation, even under occlusions or heavy smoke conditions. Simultaneously, UAV swarms guided by reinforcement learning and vision-based coordination have enabled intelligent decision-making and adaptive flight in uncertain terrains. Despite these advancements, there remains a need to unify efficient area partitioning with sensor-driven detection and practical simulation for deployment-readiness.

This study proposes a drone-assisted wildfire detection system leveraging centroidal Voronoi tessellation for optimal area coverage, integrated with thermal imaging and RGB-D data for accurate fire localization. The system is validated through MATLAB simulations and implemented in the ROS-Gazebo environment using hector quadrotor UAVs. By addressing both algorithmic efficiency and sensor integration in a simulated forest fire scenario, the study aims to bridge the gap between theoretical models and real-world readiness for UAV-based wildfire management. A study and simulation of this algorithm will aid us in finding if there is a more efficient way to carry out search and rescue/surveillance in remote places that are inaccessible or tough to enter by human beings by unmanned aerial vehicles like quad/multirotor copters. This will help avail more data for disaster management and search and rescue in the foreseeable future.

The research contribution of this work is the development and simulation of a multi-UAV system for wildfire monitoring using ROS and Gazebo, integrating thermal and RGB-D sensors for fire detection. This study addresses the coordination of UAVs through Voronoi-based partitioning and evaluates the system's performance in a controlled simulation environment. Furthermore, it identifies key challenges related to real-time control, sensor limitations, and environmental factors, providing a foundation for future work on adaptive path planning and multi-modal sensor fusion to enhance wildfire detection and response capabilities.

II. MOTIVATION

The increasing prevalence of unmanned aerial vehicles (UAVs) in diverse applications such as wildlife monitoring, disaster relief, infrastructure inspection, and surveillance highlights their growing significance in autonomous operations. UAVs have been widely adopted due to their ability to operate in hazardous and inaccessible environments, minimizing risks to human operators while enhancing efficiency and data accuracy. In particular, their use in wildfire monitoring and suppression has gained attention, as early detection and rapid response are critical in mitigating catastrophic damage. This study aims to harness the capabilities of multiple autonomous UAVs to perform wildfire surveillance and suppression tasks in a coordinated and interference-free manner. One of the primary challenges in multi-UAV operations is ensuring efficient area coverage while avoiding redundant efforts or gaps in monitoring. By employing Voronoi partitioning, the UAVs autonomously divide the affected region into distinct zones, each assigned to a specific drone. This method ensures that each UAV operates within its designated space, reducing uncertainty and maximizing coverage efficiency. Such an approach not only improves real-time monitoring but also facilitates faster decision-making in wildfire suppression. Additionally, automation plays a key role in reducing human errors associated with traditional wildfire monitoring techniques. Manual operations often suffer from delayed response times, inconsistent data collection, and increased risks to personnel. In contrast, UAV-based autonomous surveillance ensures continuous monitoring with minimal latency, allowing for quicker identification of fire outbreaks and hotspots. Furthermore, real-time data gathered by UAVs can be integrated with AI-based analytics to predict fire spread patterns, aiding firefighting teams in deploying resources more effectively. As industries increasingly shift towards automation, the adoption of autonomous UAV networks aligns with the broader trend of integrating AI-driven systems into emergency response frameworks. This transition enables the development of a safer, more scalable, and efficient approach to disaster management. By optimizing resource allocation, minimizing operational risks, and enhancing situational awareness, UAV-based wildfire monitoring and suppression contribute to making emergency response systems more reliable and effective.

III. DEVELOPMENTS TILL NOW

Since Unmanned Aerial Vehicles have, as of late, been unveiled as accessible for public use, there has been an enormous measure of exploration and experimentation concerning their handiness in everyday exercises, mostly to automate certain operations and surveillance and get a new viewpoint (in a real sense) on old issues. There has been a developing need to utilize drones with different abilities for various public and military applications, including search and salvage missions, ecological security, mailing and conveyance, active weapon engagement, space, marine robots, etc. The utilization of UAVs in firefighting applications is explicitly underlined in this paper. An opportunity to stifle a wildfire is essential as it causes monetary, ecological, and social misfortunes. Until today, UAVs were utilized by a few local groups of firefighters in some parts of the world for search and salvage activities, identification of fire break-out zones and setting off an alert to signal firefighters, determination to decide the fire's area and degree, and keeping tabs on its development, and anticipation foreseeing the fate of the fire by using remote-sensing capabilities via incorporated sensors and processing units. There has been a lot of research on utilizing UAVs based on technical and non-technical perspectives [3]-[7].

The path that covers all the points of a defined area or volume while avoiding all the hurdles is determined by coverage path planning (CPP). CPP is used in numerous robotic applications. Vacuum cleaning robots, painter robots, autonomous underwater vehicles that create image mosaics, demining robots, lawnmower robots, automated harvesters, window cleaning devices, and complex underwater structure inspectors are some robot-aided applications that use this task. Previous evidence on CPP in the literature defined all the requirements a robotic device must meet to perform the coverage task [8]-[10].

The requirements are as follows:

- Robots must cover all points in the entire target area.
- Robots must move through the region without overlapping paths.
- There should be a continuous and sequential operation without repeating pathways.
- Robots should be able to skip all obstacles.
- Simple motion trajectories like straight lines and circles must be used as they simplify control operations.
- There should be an 'optimal' path under available conditions.

Autonomous agents have been employed in specific robotics and unmanned aerial vehicle fields. Such tasks as land mine spotting and elimination, environmental surveying, emergency rescue operations, and many more [11]-[14].

In the research article [15], the authors suggested that since UAVs have a very restricted flight season of approximately only ten minutes and operations like search and salvage missions, firefighting, etc., require a large area to be covered in the most minimum time, which is not possible with a single drone. They studied the utilization of various UAVs instead of one UAV with reliable wireless networking between the UAVs and communications to the base [16]. Their research focuses on autonomous multi-UAV systems that could work with minimum human interaction. Different levels of autonomy and different degrees of centralization are required for other applications. They depicted and tested a framework of UAVs adjusted to the various situations to work according to varying levels of autonomy based on the operator's interest. Particular nodes such as a UAV or the base could join or leave the network without hampering it or influencing the mission's objective. This prevented individual failures and made the system expandable to add different types of UAVs if necessary. It also enabled the operator to intrude and change the mission plan with GUI at the base. [17] conducted controlled experiments to determine the efficiency of fire extinguishing balls for firefighting. These balls were delivered to the experiment location via UASs. The objective of their investigation was to design and test the capabilities of a UAV firefighting system. The results of their experiments suggested that firefighting balls are a better suppressant than water. They also inferred that water damage is more devastating to buildings and that using fire suppressant balls would assist in sustainable water use. The researchers closely worked with firefighters to understand how drones drop fire extinguishing balls in different situations. They tested the balls in building space and on a small patch of grass. They found that the results were extremely promising in the latter case. Hence, they concluded that extinguishing wildfires with fire extinguishing balls by dropping them to optimal points via multiple drones on time can be efficient and beneficial [18]. An algorithm to plan the path of drones was required to drop the fire extinguishing ball at optimal points. There are many algorithms available to plan the UAV path. The most common ones are Ant Colony Optimization and Voronoi Partition.

Ant colony optimization is an algorithm for determining ideal UAV paths in a similar manner that ants follow when they search for food. The ants, at first, start wandering randomly to get to the food. When an ant finds a food source, it travels back to its colony, leaving "markers" (pheromones), implying that the path reaches the food source. When other ants find these markers, they start following the trail with a certain probability of finding food at the end. This populates this path with many markers as other ants return the food. As more and more ants find food sources, a couple of streams of ants travelling to various food sources are formed in the colony. As insects leave pheromones every time they carry food, shorter paths are more robust because pheromones tend to evaporate with time. If the course is longer, the pheromones disappear before other ants take that path. The smell is thus more pungent in the shorter routes, hence optimizing the "solution". Along with this, some ants still randomly keep looking for closer food sources. Once one food source is consumed, its route becomes less populated with pheromones and eventually decays. The ant colony uses an extremely dynamic system, and its algorithm works perfectly with landscapes and maps with different topologies. Some of these systems are computer networks and artificial intelligence simulations of UAVs. [19] To keep away from the hazardous regions and save fuel and time, it is imperative to determine an optimal way from the base to the target area. The Voronoi Partition algorithm is implemented for path planning for numerous applications as it is conveniently built to fit constant time computing processes and get some optimal drone paths. [20] This paper requires the assistance of multiple drone systems to detect the fire-affected area accurately. Three quadcopters - the Asctec Hummingbird, Asctec Pelican, and the Hector Quadrotor were considered potential robots for the operation. The Asctec Hummingbird is a nifty little quadcopter generally utilized for vision-based applications. It has a small body, is lightweight, and has a flight time of 20 minutes per charge. A few additional quadcopter features include automatic landing and GPS [21]. The Asctec Pelican is a quadcopter with a 1.6 GHz Intel Atom processor and works seamlessly with the Ubuntu-operated ROS. The quadcopter enables real-time processing of visuals captured from the camera for their analysis, eliminating the requirement of an external computer for computation [22]. The authors chose the hector quadrotor from a list of numerous other ROS UAVs as it is an open-source package with numerous advanced features. The requirements of this work make Hector the most optimal choice. The Hector Quadrotor was simulated by a team at the Technical University of Darmstadt. The quadrotor is enclosed in the hector quadrotor meta package. It contains the URDF description for the quadrotor UAV, its flight controllers, and launch files for running the quadrotor simulation in Gazebo. In order to further speed up the process, the authors of [23] suggest a method for implementing multi-robot coordination between the vehicles while also simulating the detection of life during sudden onset of disasters with the aid of a deep learning model and a suitable region-partitioning technique. With its advanced use, the user of the Hector can record sensor data like Lidar, depth Camera, etc. The simulation of this quadrotor is also used to test flight algorithms and control approaches in simulations. Aerial manipulation has been developed thus far and categorized based on workspace arrangement and function. Two independent CNNs are able to be employed to determine the worker's image aspects relying on the AlexNet model, and the degree of feature abstraction enables it to reflect the key image features more accurately.

The multi-UAV systems of the Hector Quadrotors are equipped with thermographic cameras that use infrared radiations to create electronic images that identify the areas with high surface temperature, i.e., the areas affected by the fire. Numerous infrared cameras like the FLIR A35 and FLIR A65 are studied to determine the best ones with the Hector Quadrotor. The FLIR A35, a thermal imaging temperature sensor, is often used for conditions monitoring, quality assurance, process controls and sometimes even for fire prevention applications. The FLIR A35 offers visual temperature monitoring and can easily integrate into existing systems. The A35 is a small device with dimensions of 4.1 × 1.9 × 1.8 inches, making it compatible with small areas like drone systems [24], [25]. The FLIR A65 is very similar to the FLIR A35. However, it offers a larger lens of 13mm within the small dimensions of 4.1 × 1.9 × 1.8 inches. This thermal imaging temperature sensor is helpful for quality assurance and process control. It works best for fire detection and prevention with drones [21]. The most valuable feature of the

FLIR A65 is the condition monitoring technology that offers comprehensive visual temperature monitoring, perfect for disaster management [26], [27]. This paper aims to take inspiration and implement the learnings from the above studies and research to design and optimize a drone-assisted wildfire-fighting system in a robot operating system. This study outlines a technique to develop a heat map for safety assessment from images captured by a single on-board camera.

The research [28] focuses on utilizing drones and artificial intelligence, specifically reinforcement learning algorithms, to combat wildfires. The study compares the performance of DQN, Rainbow DQN, and FQF algorithms in controlling swarms of two and four drones in simulated and realistic wildfire scenarios. Results show that DQN and FQF outperform Rainbow DQN, with FQF facing challenges in certain scenarios. The study emphasizes the importance of testing algorithms with larger swarm sizes for scalability. [29] proposes a solution to track dynamic wildfire boundaries using UAVs. The wildfire boundary is modeled as the zero-level set curve of an implicit function and approximated with radial basis functions. The propagation of the wildfire boundary is modeled using the Hamilton-Jacobi equation. To navigate UAVs to the wildfire boundary, an analytical velocity vector field is constructed using radial basis function thin-plate spline. Computer simulations with a single UAV and multiple UAVs have been conducted, and the results show that the proposed algorithm can successfully track an arbitrarily shaped wildfire boundary. The article [30] presents a fire warning and suppression system using reinforcement learning (RL), comprising an energy-harvesting SUAV for fire detection and multiple ground-based FUAVs for fire extinguishing. The proposed DQL-based trajectory design problem optimizes FUAV deployment, enhancing firefighting efficiency and speed, ultimately protecting lives and properties. The paper [31] introduces a cooperative navigation strategy for networked UAVs, featuring an adaptive circular formation control protocol, task reassignment algorithm, formation reconfiguration method, and collision avoidance algorithm. It addresses unknown disturbances and actuator faults, with a forest fire monitoring simulation case study demonstrating its application potential. [32] Introduces a cooperative navigation strategy for networked UAVs, featuring an adaptive circular formation control protocol, task reassignment algorithm, formation reconfiguration method, and collision avoidance algorithm. Validation was done through a forest fire monitoring simulation and outdoor/indoor flight experiments. A self-sufficient, low-cost wildfire mitigation model (SL-PWR) optimized UAV monitoring using predicted spatio-temporal wildfire probability maps, improving situational awareness and detection speed [33]-[36]. To address the limitations of traditional fire detection methods, a UAV-assisted mobile edge computing system was proposed, featuring a lightweight fire target detection model for real-time segmentation and rapid-fire location estimation [37]. Additionally, UAV-IoT networks have been explored for optimizing fire detection probability while balancing system costs [38], and a surface flame detection model based on ATSS has been developed to enhance real-time wildfire assessment using edge computing, achieving state-of-the-art performance in flame extent evaluation [39].

Recent advancements in wildfire detection utilize UAV-based deep learning frameworks to enhance early fire identification and situational awareness. A novel ORB-SLAM-feature filtering framework integrates aerial onboard visual-infrared sensor processing and UAV navigation to estimate wildfire distance and improve geo-location accuracy [40]. The AF-Net model addresses class imbalance in UAV imagery using object-contextual representations, achieving high segmentation accuracy for active fire detection [41], while a Bayesian inference-based path-planning approach with ResNet-based detection optimizes UAV search efficiency for locating fire spots [42]. Additionally, an Adaptive Hierarchical Multi-Headed CNN with an attention mechanism improves wildfire classification accuracy [43], and a multi-modal UAV-collected dataset combining RGB and thermal imaging enhances fire detection and segmentation methodologies [44]. Unmanned aerial vehicles (UAVs) play a crucial role in forest fire detection and mitigation, leveraging deep learning (DL) and swarm intelligence for enhanced accuracy and response time. YOLOv5-s, with an improved CSP module and PAN layers, achieves 97.4% accuracy in differentiating fire and non-fire regions, reducing false positives and processing time [45]. DPMNet integrates a dual-path backbone with MiFPN and CEAFM for precise remote sensing fire detection, enhancing feature fusion and spatial perception [46]. Additionally, a regular virtual tube approach ensures safe UAV navigation in dynamic fire scenarios [47], while the MSCIDC approach accelerates fire detection and suppression using cooperative multi-UAV swarms, reducing burned area by 65% [48]. Lastly, FCLGYOLO improves UAV-based fire detection by constraining positive sample features and enhancing object positioning, performing well even in heavy smoke or occlusions [49]. In dynamic UAV networks for wildfire detection and monitoring, bio-inspired localization (BIL) and clustering (BIC) schemes using a hybrid gray wolf optimization (HGWO) method are proposed to enhance localization accuracy and energy efficiency [50]. A cooperative UAV-based target search strategy leveraging particle swarm optimization (LoPSO) improves detection efficiency and reduces search time in unknown environments [51]. Visibility-based path planning (VPP) is introduced to maximize terrain coverage during UAV flights, achieving high visibility in real-world tests [52]. UAV-based fire detection methods integrating machine learning, IoT, and WSN technologies enhance real-time detection and reduce false alarms, while a reinforcement learning-based approach optimizes UAV trajectories for fire suppression [29], [53]. Additionally, UAVs equipped with advanced sensors enable real-time air quality monitoring, efficient data collection planning for forest fire monitoring, and improved urban building segmentation using deep learning models [54]-[57]. The increasing frequency of wildfires due to climate anomalies has led to significant advancements in UAV-based wildfire detection and analysis. Recent studies have enhanced deep learning models, such as YOLOv7-tiny with CBAM, to improve fire segmentation and fire front interpretation, achieving a 3.8% improvement in detection precision and a segmentation frame rate of 64.72 Hz [58]. Additionally, synthetic wildfire datasets like MSFWD have been developed to address challenges in varying terrain, lighting, and weather conditions, aiding fire detection algorithms [59]. AI-enabled UAV systems now support wildfire management across pre-fire, active-fire, and post-fire stages, integrating ML, RL, and DL techniques for monitoring and response planning [60]. Novel approaches, such as SegNet-based image classification and wireless sensor nodes with AI classifiers, have further enhanced early wildfire detection capabilities [61], [62]. Moreover, high-resolution wildfire models, including FDS-LS, have demonstrated the impact of wind dynamics on fire spread, and UAV-based wind field measurements have been proposed to refine fire propagation models [63]-[65]. Real-time geospatial mapping using deep CNNs and LSTMs has significantly improved the prediction accuracy of fire spread patterns, assisting emergency response teams [66]. Furthermore, UAV-based LiDAR and thermal imaging have been integrated with deep learning frameworks to detect fire hotspots with higher precision and reduced false positives [67]. These advancements collectively contribute to real-time wildfire detection, improved modeling accuracy, and enhanced disaster management strategies [68].

The deployment of UAV-mounted base stations (BSs) has gained traction due to their ability to extend cellular network coverage efficiently, offering cost-effective solutions in areas with coverage gaps [69]. Similarly, UAV-IoT systems are being explored for wildfire detection and management, leveraging LoRaWAN-based architectures for real-time fire classification and tracking, achieving an accuracy of 99.46% [70]. In wildfire emergency response, a novel cooperative search and coverage (CSC) strategy using near non-dominated solutions has been introduced, optimizing UAV-based fire hotspot detection through probability pattern matching [71]. Additionally, UAV-based remote sensing is proving effective in monitoring agricultural practices, particularly in detecting rice straw burning through multisensory fusion techniques, improving YOLOv5 detection accuracy by up to 5% [72]. Wildfire smoke detection (WFSD) is crucial for environmental safety, and recent research explores deep learning models for enhanced detection accuracy. Attention-based YOLOv5 models incorporating efficient channel attention (ECA), Global attention module (GAM), and coordinate attention (CA) have demonstrated improved robustness, with GAM achieving a 95% F1 score [73]. Computer vision-based wildfire detection methods, particularly CNNs like YOLOv5, Inception v3, and Faster R-CNN, are widely used, but challenges remain in deploying satellite systems for real-time monitoring [74]. UAV-based detection using YOLOv7-MS integrates a 3FIoU loss function and FasterNet, achieving a mAP of 79.3% at 175 fps [75]. Remote sensing approaches, leveraging Sentinel and PlanetScope imagery, effectively assess post-wildfire severity, correlating vegetation loss with carbon monoxide levels [76]. FireXnet, a lightweight deep learning model, enhances wildfire detection efficiency, outperforming VGG16 and InceptionV3 while integrating SHAP for explainability [77]. Vision Transformer-based FWSRNet improves wildfire recognition, achieving 94.89% accuracy, demonstrating its effectiveness in IoT-enhanced monitoring [78]. UAS-based real-time path planning optimizes wildfire perimeter monitoring, addressing the dynamic nature of fire spread [79]. Adaptive multi-sensor fusion techniques, integrating LiDAR and thermal imaging, enhance early wildfire detection accuracy [80]. Advanced deep reinforcement learning methods improve UAV-based surveillance efficiency, enabling autonomous navigation in wildfire-prone areas [81]. Hybrid models combining CNN and LSTM architectures enhance smoke detection by capturing spatial and temporal features [82]. Transformer-based models such as Swin Transformer outperform traditional CNNs in wildfire detection tasks, achieving higher precision and recall Edge computing-enabled WFSD frameworks reduce latency and improve real-time decision-making in remote wildfire-prone regions [83].

IV. METHODOLOGY

A. ROS-Based Deployment of Quadcopters Using Centroidal Voronoi Tessellation

Centroidal Voronoi Tessellation (CVT) was employed for optimal positioning of UAVs to ensure equal-area distribution for wildfire surveillance. The algorithm iteratively places each UAV at the centroid of its corresponding Voronoi cell to minimize overlap and redundancy. This deployment strategy was simulated in MATLAB and implemented in ROS-Gazebo using Hector Quadrotors. However, it is important to note that the CVT-based optimization currently assumes a static or quasi-static environment. In real-world wildfire scenarios, the dynamic nature of fire spread—driven by factors such as wind speed, humidity, and terrain variability—may render static Voronoi partitions suboptimal over time. A critical limitation of the current approach is its inability to adapt autonomously to rapidly changing spatial conditions. To address this, future work will explore dynamic Voronoi partitioning with real-time updates triggered by thermal feedback and environmental sensors.

Voronoi partitioning plays a crucial role in the optimal deployment of UAVs for wildfire detection. The centroidal Voronoi tessellation (CVT) method ensures that UAVs are positioned at the centroid of their respective Voronoi cells, resulting in an unbiased search distribution. Each partitioned region is associated with a single UAV, ensuring uniform coverage. This configuration inherently encodes proximity information, allowing efficient decision-making regarding spatial relationships, such as determining the nearest object or estimating inter-agent distances. The UAV deployment process is initiated with an arbitrary distribution, followed by an iterative optimization process that adjusts UAV positions to their respective Voronoi centroids. This ensures equitable area coverage and minimizes redundant overlap. The implementation involves a simulation of 50 UAVs, with scalability to various fleet sizes (e.g., 5, 10, 15, 25, 30). The importance of Voronoi-based coverage lies in its ability to reduce computational complexity, as it eliminates the need for continuous distance queries, optimizing response time for fire detection.

Algorithm 1: Voronoi-Based UAV Deployment

Input: UAVs' initial positions P= {p1, p2, ..., pn} P = \{p_1, p_2, ..., p_n\}P={p1,p2,...,pn}

Output: Optimized UAV positions

Initialize UAV positions randomly within the region of interest.

Compute Voronoi partitioning for given UAV positions.

For each UAV iii do:a. Compute its centroid CiC_iCi of the Voronoi region.b. Move UAV to CiC_iCi.

Repeat steps 2–3 until convergence.

Return final UAV positions.

Here from Fig. 1 and Fig. 2 (a) the initial configuration of multiple UAV's, we scatter into a proper (i) Voronoi configuration. This simulation consists of 50 drones, but a simulation of the 'n' number of drones, be it 5, 10,15, 25, 30, and many more, is possible. The sole reason for using Voronoi is that this type of configuration encodes proximity information that helps answer questions like "Which object is closer to X?" "How far is X from Y."

Thus, this will aid in performing an equal search to detect the fire using the hector quadcopter. Without the Voronoi, the concerned application will fail to work in the real world because there will be an increase in difficulty. After all, distance queries will have to be computed every time, wasting precious time and consequences that must be prevented most of the time.

n sites = n faces

2n-5 = vertices

3n-6 = edges

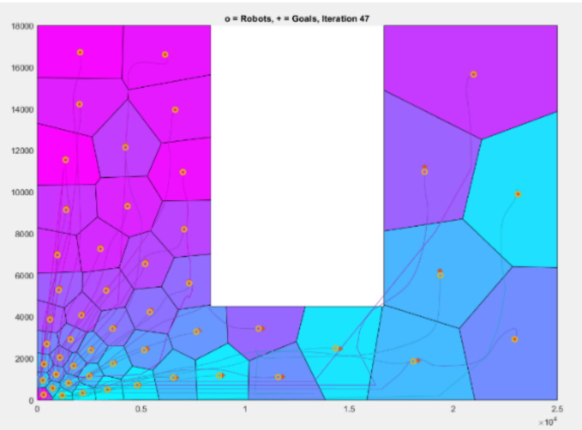

Fig. 1. Initial configuration of multiple UAVs

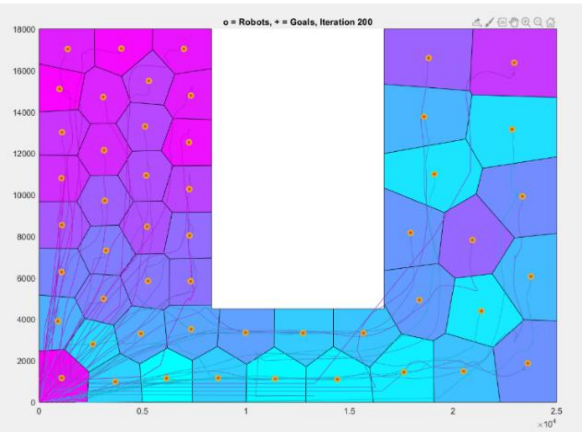

Fig. 2. Configuration of n drones after applying Voronoi tessellation

B. Data Collection from the Sensors using Pyroelectric Sensors

Fire detection in UAV-based surveillance systems relies on pyroelectric infrared (PIR) sensors, which are well-suited for non-contact temperature monitoring. These sensors detect infrared radiation emitted by fire and can estimate temperature variations over large areas. The advantages of PIR sensors include rapid response times, durability, and suitability for harsh environmental conditions. Additionally, they can detect fires in obstructed areas, such as dense forests, where visibility is limited. To ensure accurate data collection, the UAVs continuously monitor temperature variations, differentiating fire-induced infrared signatures from background noise. This is achieved through adaptive thresholding techniques and machine learning-based anomaly detection.

C. MATLAB and ROS Interface

The integration of MATLAB with the Robot Operating System (ROS) facilitates real-time control and simulation of UAVs in the wildfire detection system. The MATLAB-ROS interface enables UAVs to receive positional updates, compute Voronoi-based movement trajectories, and execute flight commands based on predefined waypoints. The integration process involves several trials to refine the control strategy:

- Trial 1: Direct Velocity Commands via MATLAB-ROS

Initially, UAVs were controlled by sending velocity commands directly from MATLAB to ROS. However, this approach led to inaccuracies due to incorrect time estimations in Voronoi calculations. The velocity computation was defined as:

$$v = (x2 - x1)/t \tag{1}$$

where x_1 and x_2 represent initial and final UAV positions, respectively. This method failed due to inconsistent time intervals, leading to erroneous movement predictions.

- Trial 2: Desired Position Commands via MATLAB

To address the inaccuracies in velocity control, the next trial involved sending desired goal positions instead of velocity commands. The UAVs were instructed to move to specified coordinates, improving control precision. However, MATLAB's ROS action client presented compatibility issues, limiting its effectiveness.

- Trial 3: MATLAB to Python Node Communication

A Python ROS node was introduced as an intermediary to overcome MATLAB's ROS action client issues. Instead of sending positions directly, MATLAB published goal configurations to a custom ROS topic, which was then processed by the Python node. The Python node relayed these commands to the UAVs, improving communication reliability. However, tracking errors and ensuring seamless goal execution remained challenging.

- Final Trial: Offline Path Planning and Execution

The final approach involved precomputing UAV trajectories offline. MATLAB generated goal configurations stored in a CSV file, which was later read by the Python node. The Python script then executed UAV movements based on these precomputed paths. While this method successfully improved UAV control, it introduced latency due to sequential movement execution. To enhance efficiency, an asynchronous execution strategy was adopted.

Algorithm 2: Offline UAV Path Planning

Input: Initial UAV positions, target coverage area
Output: Optimized UAV paths

Generate Voronoi-based goal configurations in MATLAB.

Store the goal positions in a CSV file.

Initialize the Python ROS node.

Read the CSV file in the Python node.

For each UAV iii: a. Send goal position to ROS action client. b. Execute motion command asynchronously.

Monitor UAV positions until all reach their goal.

This methodology ensures efficient UAV deployment, real-time fire detection, and robust communication between MATLAB and ROS, optimizing wildfire monitoring using UAV-based surveillance.

The integration of MATLAB and ROS in the proposed UAV wildfire monitoring system offers an innovative approach to leveraging advanced control algorithms within a robotics middleware framework. However, this integration currently faces several unresolved challenges that affect system reliability and real-time performance. Initial attempts to control UAV motion using velocity-based commands exhibited significant tracking inaccuracies, prompting a shift towards position-based goal commands via MATLAB's ROS action client. Although this transition reduced some timing errors, fundamental compatibility issues within MATLAB's ROS interface persisted, resulting in sporadic communication failures and delayed command execution. To mitigate these problems, a Python intermediary node was introduced to handle ROS communication, thereby improving message handling and reducing direct dependency on MATLAB's ROS client. While this solution enhanced communication robustness, it increased system architectural complexity, introducing an additional layer that may contribute to latency and potential points of failure during live deployment scenarios. Furthermore, the current reliance on precomputed UAV trajectories stored in CSV files imposes significant constraints on operational flexibility. The asynchronous execution of these trajectories limits the system's ability to dynamically adapt to evolving wildfire conditions, potentially degrading coordination efficiency during critical monitoring tasks. This static approach lacks the responsiveness necessary for real-time path planning and adaptive re-tasking, which are essential for effective wildfire surveillance and rapid response. In terms of sensing, the utilization of pyroelectric infrared (PIR) sensors for fire detection presents inherent limitations. PIR sensors are prone to reduced sensitivity when detecting low-intensity fires and are susceptible to false positives triggered by environmental heat sources such as sunlight reflections or heated terrain. This compromises detection accuracy and reduces overall system reliability in diverse field conditions. Recognizing these limitations, the methodology now underscores the importance of integrating multi-modal sensing approaches. Specifically, the fusion of thermal imaging, RGB visual data, and contextual environmental analysis, enhanced by AI-driven filtering algorithms, shows promise for improving detection precision and minimizing false alarms. In summary, while the current MATLAB-ROS integration and sensing framework demonstrate proof-of-concept viability, several critical limitations remain. The revised approach advocates for a transition toward fully ROS-native or Python-centric control frameworks to simplify architecture and improve responsiveness. Additionally, the adoption of adaptive online trajectory planning and multi-sensor data fusion is essential to address the dynamic, uncertain nature of wildfire environments. These enhancements are vital for advancing the practical applicability and robustness of UAV-based wildfire monitoring systems in real-world deployments.

D. *Limitations of Offline Path Planning*

Initial trials involved direct velocity control and real-time position updates through MATLAB-ROS integration. Due to timing inconsistencies and communication issues, the final methodology relied on offline precomputed goal configurations, which were executed sequentially by a Python ROS node. While this improved control accuracy, it introduced a significant limitation—latency. In wildfire response, early detection and immediate reallocation of resources are critical. Offline planning restricts the system's responsiveness to new fire outbreaks or environmental disturbances. To mitigate this, future implementations will focus on online, asynchronous path planning coupled with onboard decision-making.

E. *Scalability and Sensitivity to UAV Density*

Scalability was explored by simulating deployments with varying UAV fleet sizes (e.g., 5, 10, 25, 50 units). While these simulations showed promising coverage performance, no formal sensitivity analysis was conducted to quantify the impact of increasing drone density on system robustness, communication bandwidth, or processing latency. Additionally, inter-drone coordination complexity and collision avoidance were not modelled. In large-scale real-world deployments, these factors may introduce bottlenecks that compromise both safety and efficiency. Future studies will include systematic scalability analyses and adaptive swarm coordination strategies.

F. *Environmental and Operational Constraints*

Although thermal imaging sensors and simulated wildfire conditions were tested in ROS-Gazebo, the system's performance under real environmental conditions such as heavy smoke, wind turbulence, GPS signal loss, and sensor degradation was not evaluated. Communication delays in forested or mountainous terrains can further reduce system reliability. These factors need to be addressed through hardware-in-the-loop testing, real-time sensor fusion, and redundancy in communication protocols to ensure practical robustness.

V. RESULTS

A. MATLAB Simulation of Voronoi

The central control is being implemented in MATLAB. The MATLAB program running in 'Machine2' speaks with the ROS climate in 'Machine1' to acquire the current position and directions of the quadcopters and the current uncertainty by every one of the quadcopters. Voronoi cells are computed on the current arrangement of the multi-quadcopter framework, which is read through the topics. The MATLAB simulation with 'n' number of drones falling into Voronoi tessellation and acquiring equal-area like the areas are cells and then figuring out the certainty density of the quadcopter in an environment trying to detect a spot fire and take immediate action.

B. Hector Quadcopter Simulation in ROS

A simulated quadrotor in the ROS Gazebo environment is developed to get closer to the objective. This approach utilizes a simulated hector quadrotor in a Gazebo environment. The most challenging piece of unravelling about flying robots is the congruous pummeling. The subsequent disappointments can incur a considerable expense from broken equipment parts, from learning flight control interestingly to testing new equipment or flight calculations. A recreated air vehicle planned and created for ROS is ideal to answer this trouble. Because the noetic distribution of ROS was released recently, most packages and meta-packages are not supported yet. To overcome this, the Hector Quadcopter is built from the source while solving the errors and problems that arose from a lack of updated support. Fig. 3 shows hector Quadrotor Package's RQT graph depicting each node and topics for ROS Simulation.

The simulation closely represents the real-world flight of the quadrotor. The simulated quadcopter could be controlled by both the keyboard and directly sending commands to the nodes through the topic. Fig. 4 shows the /cmd_vel topic to broadcast the drone for control. The most efficient way to detect a fire is to use a thermal sensor. Attaching and testing various thermal sensors, including a generic thermal sensor, seek thermal compact, FLIR a35 and FLIR boson 640. Connecting different thermal sensors lets us compare the performance of the drone and camera combinations in various scenarios and gives more flexibility and options. Pictures of the drone attached with a thermal compact camera and FLIR A35 are shown below. Fig. 5 shows the Hector quadrotor connected to a FLIR 35.

Thermal imaging temperature sensor: The FLIR A35 produces high-quality, 81,920-pixel thermal images showing temperature differences as small as 50 mK. This allows easy tracking of temperature changes, whether your application is process control/quality assurance, condition monitoring, or fire prevention. At just 4.1 × 1.9 × 1.8 in, the A35 brings thermal imaging to your smallest spaces. It is possible to add the sensor by editing the quadrotor's launch file. The image from the thermal sensor can be visualized in Rviz. The camera's output is live and can be viewed, as shown in the Fig. 6.

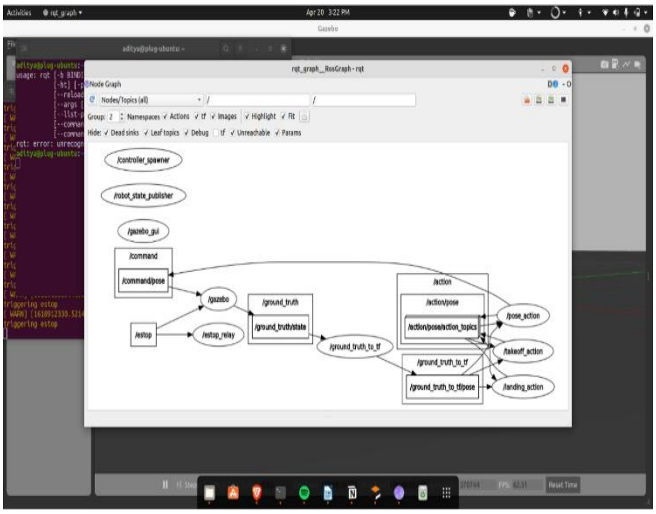

Fig. 3. RQT graph of hector quadrotor package showing all the nodes and topics

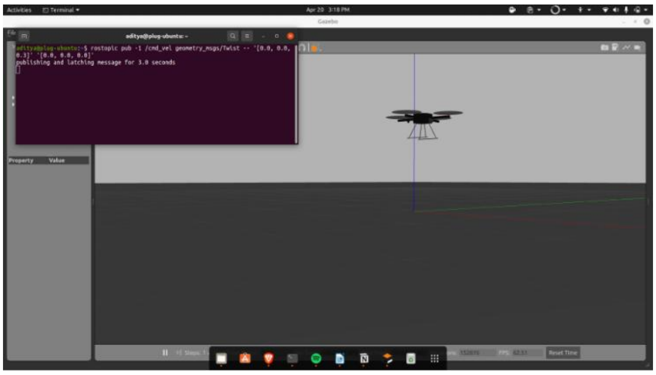

Fig. 4. Controlling the drone by publishing it into the /cmd_vel topic

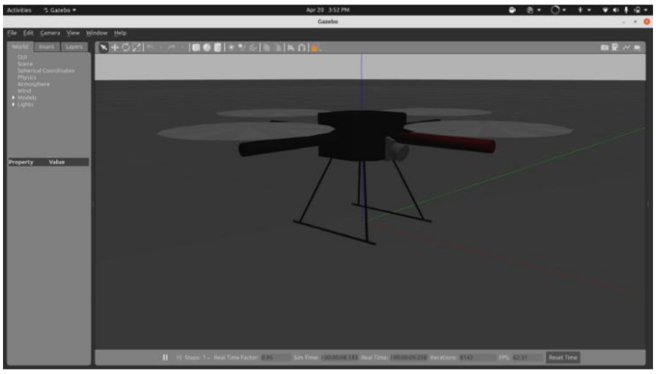

Fig. 5. Hector Quadrotor attached with FLIR a 35

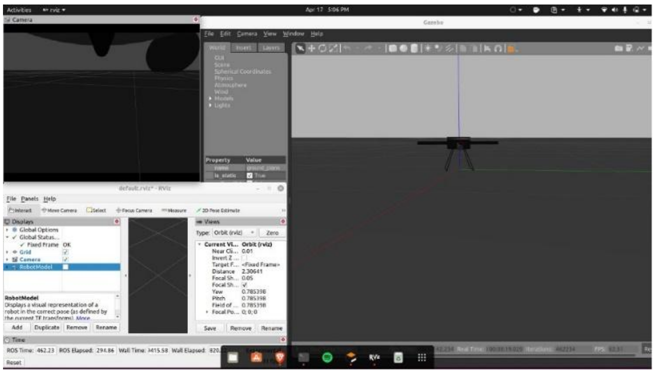

Fig. 6. Output of the camera and the gazebo view of the drone

C. Creating a Thermal Environment for Fire Detection

The aim is to create a forest environment with thermal attributes (Forest Fires) in Gazebo. Replacing the FLIR A35 with the FLIR A65 offers a larger lens of 13 mm within the small dimensions of 4.1 × 1.9 × 1.8 inches. Furthermore, by adding a depth sensor, the ASUS RGB-D Camera supplements the conventional images' depth and texture information on a per-pixel basis. On running simulations with the Hector Quadcopter and the cameras and sensors, the UAV could detect the fire-affected areas in the simulated environment. To get a more authentic result, simulating the forest with different types of trees and including trees of different shapes and sizes.

Simulating Different fire-affected areas in the forest environment in Gazebo. The green color represents the unaffected areas, whereas the red color attributes to high temperature, i.e. fire. Forest simulation employing multiple models for trees is seen in Fig. 7. The Red Trees represent the areas of the forest ruined by the fire is represented in Fig. 8.

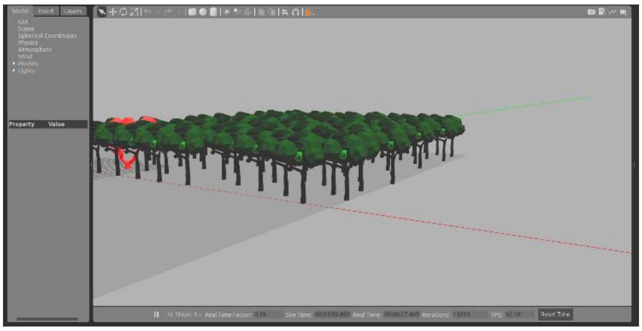

Fig. 7. Simulation of forest with different models of trees

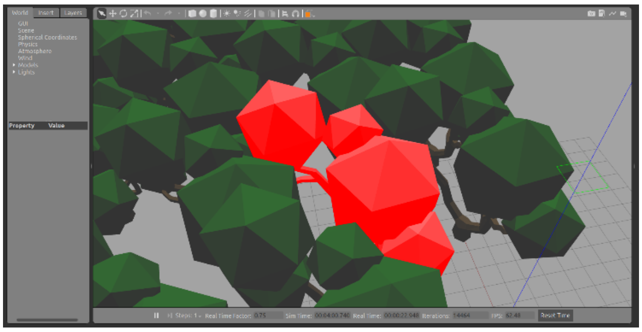

Fig. 8. The Red Trees are the fire-affected parts of the forest

VI. CONCLUSION

Drone technology offers promising advancements for wildfire monitoring and management. This study presented a simulation framework using ROS and Gazebo to deploy a multi-UAV system based on Hector Quadrotors equipped with thermal sensors such as the FLIR A65 and ASUS RGB-D cameras. The simulation results demonstrated the system's capability for fire detection and thermal imaging within a controlled environment. However, the performance limitations of these sensors—such as false-positive rates and sensitivity to varying thermal signatures—require careful consideration and further empirical validation. Our current work serves as a foundational step rather than a definitive solution, as sensor reliability in complex, dynamic wildfire conditions remain an open challenge. Moreover, while the simulation successfully demonstrates UAV coordination and environment interaction, transitioning from simulation to real-world deployment involves addressing several critical complexities. These include overcoming ROS compatibility issues, reducing latency introduced by offline path planning, and ensuring robustness under adverse environmental factors such as smoke, occlusions, and rapidly evolving fire behavior.

To advance towards practical application, future work will focus on hardware-in-the-loop testing, real-time adaptive control strategies, multi-sensor fusion for improved detection accuracy, and extensive field trials in diverse wildfire scenarios. This phased roadmap aims to bridge the gap between simulation and operational systems, facilitating effective and reliable UAV-assisted wildfire management.

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