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RESEARCH ARTICLE

Optimizing Multi-Agent Search With Non-Uniform Sensor Effectiveness in Distributed Quadcopter Systems

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ABSTRACT This article explores the vital role of distributed multi-robot systems (DMRS) in applications such as search and rescue, surveillance, and military operations. In particular, we focus on developing a method for multi-agent search using a quadcopter unmanned aerial vehicle (UAV) equipped with a downward-facing camera. Unlike existing studies, our model includes a unique model for searching for the best camera and achieving maximum performance in the scene. We introduce an uncertainty distribution that reflects the lack of information to capture the uncertainty in the search space. Using the concept of the hub Voronoi configuration, our approach optimizes the deployment of the quadcopter to reduce confusion. The distribution and detection process continues until the average uncertainty reaches a threshold, which means the detection target is successful and reliable. We present an in-depth study of the different parameters in the search for a good camera and propose a test setup for the model's performance. The multiple quadcopter search strategy was implemented and simulated using ROS/Gazebo and Matlab allowed its performance on various parameters to be verified in real experiments. Simulation results demonstrate the effectiveness of this strategy and provide insight into the impact of the study on aspects such as camera performance and number of detection quadcopters. The simulation platform we have created is an important tool for further testing and benchmarking optimization in real life. This research helps to improve the understanding of multi-sensory search strategies, especially when the sensor search efficiency is unequal.

INDEX TERMS Cooperative search, multi-robot search, quadcopter, unmanned aerial vehicles, Voronoi partitioning.

I. INTRODUCTION

The exploration of environments to locate targets of interest, particularly in disaster-stricken areas, presents a challenging yet crucial problem with practical implications. Early contributions in the literature ([1], [2], [3]) addressing target search in unknown environments often made assumptions under certain restrictive conditions. Primarily theoretical and centred around a single agent searching for static or moving targets, these seminal works lay the groundwork for subsequent investigations[4].

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This research aims to enhance the efficiency of target search tasks by introducing collaboration among multiple agents. Effective coordination becomes crucial in scenarios where various searchers operate simultaneously. Incorporating multiple agents offers advantages beyond expedited mission times, including resilience to individual robot failures due to their collaborative nature. Additionally, the simplified design and lower cost of individual robots make them valuable assets in challenging conditions, such as military operations and natural disasters. This study addresses challenges in disaster response and military applications, concentrating on two critical objectives: searching for survivors in areas affected by natural calamities and detecting mines and enemy targets. Unmanned vehicles, notably Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs) equipped with advanced sensors, play a pivotal role in achieving these objectives. Their deployment enhances the effectiveness of collaborative efforts in disaster-stricken or hostile environments.

In MAS/MRS, individual agents' coordinated actions influence each other over an adjacency graph fostering emergent collective behaviours. The system's controller can adopt centralized, decentralised, or distributed control architectures. In a centralized model, a central controller oversees all agents, posing a vulnerability to its failure. Conversely, a distributed architecture assigns each agent its controller, ensuring robustness but introducing communication overhead. Decentralized control operates with independent agent controllers, eliminating communication dependency but limiting interaction consideration. Centralized and distributed architectures require communication at different levels, susceptible to delays, while decentralized architecture avoids inter-agent controller communication.

In a series of papers, various novel frameworks and methodologies for optimizing the performance of unmanned aerial vehicles (UAVs) in diverse applications are introduced. In [5], a framework for modeling and analyzing multi-UAV persistent search and retrieval tasks in stochastic environments is presented, with a case study on park cleanup demonstrating practical applications. Meanwhile, [6] proposes a coordinated-search planning method for UAV-ground vehicle teams, specifically tailored for wilderness search and rescue missions, showcasing improved target detection rates and reduced search times. Additionally, [7] addresses optimal coordination of fixed-wing UAVs for vision-based target tracking, focusing on minimizing geolocation error covariance using stochastic fourth-order models. Furthermore, [8] presents a distributed model predictive control scheme for quadcopter formation control, integrating collision avoidance and communication topology maintenance, validated through real quadcopter experiments. Lastly, [9] introduces an artificial potential field-A* algorithm for dual-quadrotor cooperative transport systems' path planning, significantly enhancing efficiency and safety compared to traditional methods. A comprehensive review of reinforcement learning-based control systems for swarm robotics is provided in [10], offering insights into their applications, algorithms, challenges, and future directions. In [11], a novel distributed real-time search path planning method was introduced for enhancing the efficiency of multi-UAV cooperative area search operations. By integrating distributed model predictive control (DMPC) framework and employing a distributed stochastic algorithm based on enhanced genetic algorithm (DSA-EGA), the proposed approach effectively addressed local optima issues and outperformed state-of-the-art algorithms in solution quality. This study showcased improvements of 7.7 pec in search efficiency with the established DCOP model and at least 4.3 percentage efficiency enhancement with DSA-EGA, indicating high scalability and promising performance in cooperative area search scenarios. Similarly, in [12], a novel approach leveraging Glasius bio-inspired neural network (GBNN) and distributed model predictive control method was presented for addressing constraints in multirobot systems performing region coverage search tasks. Experimental validation confirmed the effectiveness of the proposed approach, showcasing superior performance compared to established algorithms in multi robot region coverage search tasks. Furthermore, [13] addressed limitations in existing algorithms for Multi-Agent Active Search (MAAS) by proposing a novel reinforcement learning-based approach. By framing MAAS as a reinforcement learning problem in the belief space using a Poisson Point Process formulation, the proposed method exhibited robustness to test-time miscommunication, offering promising advancements in MAAS. These studies collectively contribute to advancing the capabilities of search and exploration tasks in autonomous systems, addressing critical challenges and opening new avenues for research and development in the field. This paper presents a novel method for multi-agent search utilizing quadcopter unmanned aerial vehicles (UAVs) equipped with downward-facing cameras, crucial for applications like search and rescue. The approach incorporates an uncertainty distribution to capture the uncertainty in the search space and optimizes quadcopter deployment using the hub Voronoi configuration to reduce confusion. Through simulation and real experiments, the effectiveness of the strategy is demonstrated, providing insights into improving multi-sensory search strategies, particularly when sensor search efficiency varies.

The current state of research in multi-agent systems (MAS) and multi-robot systems (MRS) for target search and exploration tasks leaves several important gaps that necessitate further investigation. Firstly, there is a noticeable absence of comprehensive studies focusing specifically on disaster response and military applications, despite the significant advancements made in other domains. While existing literature has explored theoretical models or applications in controlled environments, there is limited emphasis on real-world scenarios such as disaster-stricken areas or hostile environments. Consequently, there is a pressing need for research that addresses the unique challenges inherent in these domains and develops practical solutions for efficient target search and detection. Moreover, many existing studies overlook the inherent uncertainty in target search tasks, particularly in dynamic and unstructured environments. While some research incorporates uncertainty models, they often lack sophistication or adequately account for real-world uncertainties. This gap highlights the necessity for advanced methodologies that effectively model and address uncertainty in target search tasks, thereby enhancing the robustness and reliability of MAS/MRS systems in practical applications. Furthermore, the potential of downward-facing cameras for target detection and localization in MAS/MRS systems remains relatively underexplored. Despite offering unique advantages such as wide-area coverage and real-time monitoring, downward-facing cameras have not been extensively utilized in multi-agent search scenarios. Thus, there is an opportunity to investigate their efficacy and develop optimized strategies for their deployment in MAS/MRS systems to enhance target search efficiency. Additionally, while several studies propose novel control and optimization techniques for MAS/MRS systems, their integration into practical applications for target search tasks is often limited. Many existing approaches remain theoretical or lack validation through real-world experiments, which hinders their applicability and scalability. Consequently, there is a need for research that effectively integrates novel control and optimization techniques into MAS/MRS systems for target search and exploration tasks, ensuring their effectiveness and practical utility in diverse environments.

The research described in this paper contributes significantly to addressing several key research gaps in the field of distributed multi-robot systems (DMRS) for target search and exploration tasks. By focusing on practical applications such as search and rescue, surveillance, and military operations, the study targets areas with significant real-world implications, providing solutions tailored for disaster response and military applications. Unlike many existing studies, the research incorporates a unique uncertainty distribution model to capture the inherent uncertainty in the search space, enhancing the robustness and reliability of DMRS systems in dynamic and unstructured environments. Furthermore, the proposed approach optimizes quadcopter deployment using the hub Voronoi configuration concept, reducing confusion and maximizing performance in the scene, thereby improving search efficiency in DMRS systems. The study also implements and simulates the multiple quadcopter search strategy using ROS/Gazebo and Matlab, enabling real-world validation and performance analysis. Through simulation results demonstrating the effectiveness of the proposed strategy and in-depth analysis of different parameters, such as camera performance and the number of detection quadcopters, the research enhances the understanding of multi-sensory search strategies, especially in scenarios with unequal sensor search efficiency. Overall, by addressing these research gaps, the described research advances the capabilities of DMRS systems for target search and exploration tasks, facilitating their practical application in various domains and improving their effectiveness, reliability, and adaptability in real-world environments.

The subsequent sections of the paper are structured as follows. Section II offers an extensive review of relevant literature. Section III delineates the problem statement, while the proposed methodology is expounded upon in Section IV. Section V presents the simulation and experimental results, and Section VI provides the concluding remarks.

II. RELATED LITERATURE

Researchers from various fields have been drawn to the intriguing, practically significant, and demanding task of exploring disaster-Taskcken areas to locate targets of interest, such as survivors. Faiyaz et al. [14] have given a thorough literature survey of the past decade's developments in commercially available UAVs, covering aspects like geometric structure, flying mechanisms, sensing capabilities, and applications such as path planning and artificial intelligence. Another informative review on UAV path planning, emphasising various optimization techniques, is given in [15]. Search theory, motion planning, optimisation, sensor technology, sensor fusion, and unmanned aerial, ground, and surface vehicle technology are just a few of the fields that have contributed to this area. Exploring the efficacy of numerous cooperative agents in search missions has become increasingly important as technology has evolved, especially in autonomous vehicles, communication, sensor technology, and optimisation theory. Additional difficulties in coordinating many agents go beyond what arises with a single agent. Scholars have used various methods to tackle the multi-quadcopter search problem discussed in this research article. As evidenced by the works of [16], [17], [18], [19], and [20], some have made use of predefined lanes. This strategy aims to make path planning for the agents during the search more efficient. In [21], the authors introduce MRS Drone, a modular autonomous Unmanned Aerial Vehicle (UAV) platform designed for seamless real-world deployment of multiple aerial robots within a Multi-robot System (MRS), showcasing its unique modularity, ease of assembly and modification, and practical applicability through diverse real-world scenarios. Cooperative coverage control for a multi-UAV system is studied in [22], focusing on rapid assessment of earthquake-affected areas, where fixed-wing UAVs conduct an initial general scan followed by quadcopters for detailed information extraction and victim localization, demonstrating the effectiveness of collaborative distributed control in minimizing environmental uncertainty and achieving maximum coverage efficiency. Yuanda et al. [23] study introduces a deep learning-based visual detection architecture for extracting positional information from images captured by a cooperative unmanned surface vehicle (USV) and unmanned aerial vehicle (UAV) system in marine search and rescue operations. A reinforcement learning-based USV control strategy is proposed, showcasing improved motion control policies capable of effectively navigating through wave disturbances, which are also presented and tested. Yuanda et al. [23] introduced a deep learning-based visual detection architecture for extracting positional information from images captured by a cooperative unmanned surface vehicle (USV) and unmanned aerial vehicle (UAV) system in marine search and rescue operations. A reinforcement learning-based multi-strategy cuckoo search algorithm for UAV path planning is presented in [24]. It considered the search problem as an optimization problem. In contrast, this paper implements centroidal Voronoi partitioning in which each centroidal configuration can be viewed as an optimal solution to the task allocation problem. In [25], the authors presented a distributed cooperative search method for multi-UAV with unstable communications based on ant colony optimization. In [26], the authors addressed the problem of passive target localization using mobile unmanned aerial vehicles (UAVs), introducing a novel time-difference-of-arrival (TDOA) model for target localization and establishing a performance limit inequality between its Cramer-Rao lower bound (CRLB) and the mean-squared error (MSE). As already stated, many bio-inspired algorithms are being developed in UAV motion planning. In [27], the authors introduced the Motion-Encoded Genetic Algorithm with Multiple Parents (MEGA-MPC) using multiple Unmanned Aerial Vehicles (UAVs), employing Bayesian theory to formulate target tracking as an optimization task with the detection probability as the objective function, MEGA-MPC utilizes parallel computations and enables UAV communication. The UAV constraints, such as short battery life and moderate computational capability, are incorporated in developing an edge computing-enabled multi-UAV cooperative search mechanism in [28]. A multi-agent deep reinforcement learning (MADRL) method for collaborative target search by multiple unmanned aerial vehicles (UAVs) with limited sensing and communication capabilities in dynamic environments is given in [29]. The study also proposes a digital twin (DT)-driven training framework, "centralized training, decentralized execution, and continuous evolution" (CTDECE), for superior search and coverage rate. An enhanced image processing technique in which a Temporal Contextual Saliency (TeCS), leveraging visual saliency and incorporating a convolutional Long Short-Term Memory (LSTM) layer to analyze UAV video automatically is developed in [30] which aims at detecting anomalies and expedite the search and rescue response by efficiently processing large amounts of data. A predictive framework for multi-UAV teams, focusing on real scenarios of aerial wildfire monitoring, is presented in [31]. The methodology permits the UAVs to infer latent fire propagation dynamics and derive analytical temporal and tracking-error bounds.

In [32], [33], [34], and [35] have all used dynamic programming to optimise path planning in gridded landscapes, guaranteeing methodical exploration for improved search performance. To enhance cooperative searching, learning methods–as applied by [36], [37], [38], and [39] involve modifying strategies in light of prior experiences and results. Researchers such as [40], [41], [42], [43], and [44] have addressed the coordination among exploring robots through activities centred on the game, graph, and team theory concepts. The goal of search theoretic procedures, as demonstrated by the works of [44] and [45], is to maximise search efficiency and strategies. The likelihood of target identification and sensor fusion are handled by Bayesian techniques, as demonstrated in works by [46], [47], [48], [49], and [50]. To further optimise coverage and efficiency in the search mission, the notion of formation flying, first presented by [19], [51], and [52], change the search technique from a single search agent sweeping strategy to a multi-agent scenario. In [53], the authors introduce a collaborative air-ground team of autonomous vehicles for outdoor exploration, employing a custom multi-rotor with stereo cameras to capture imagery and construct a height map in real time. The proposed online exploration algorithm, running onboard the UAV's Nvidia TX2 GPU, autonomously guides the aerial vehicle to map unexplored areas and directs a Clearpath Robotics Jackal ground vehicle towards user-defined goals.

The type of agent determines its mobility; for example, unmanned aerial vehicles (UAVs) with fixed wings or rotors or ground vehicles with differential wheels or skid steering. Conversely, a quadcopter is not limited by a fixed-wing UAV's minimum turning radius. Because of this, the path planning method must consider the particular needs and limitations related to the selected class of agent or vehicle. The literature covers various agent kinds, from UAVs to abstract entities.

The term "agent" is often used to refer to any autonomous vehicle in practice. Examples of researchers who have used this term include [36], [37], [40], [41], [42], [43], [54], [55], [56], [57], and [58]. However, the tactics suggested in these publications are frequently more useful for UAVs outfitted with the right sensors to act as search agents. On the other hand, as evidenced by numerous studies like [54], [59], [60], [61], [62], and [63], some writers select ground vehicles, such as Autonomous Ground Vehicles (AGVs), for search missions. Galceran et al. [64] discuss autonomous underwater vehicles (AUVs), but [65] use autonomous surface vehicles (ASVs/USVs). Kolling et al. [66] introduce a novel method with a human agent directed by the established search methodology. While heterogeneous vehicles are introduced in some publications, most literature typically uses homogeneous search agents and sensors. Also [67], [68], and [69] are few studies that use a combination of search and service unmanned aerial vehicles (UAVs) and UAVs.

Along with agent selection, the choice of sensor is an essential factor in the formulation of MAS issues. The nature of the target being sought often dictates the sort of sensor to be used; for instance, a thermal sensor may be appropriate for spotting a forest fire. While many studies in the literature, including those by [58], frequently consider an abstract target detection mechanism and a generic sensor, some researchers concentrate on particular search sensors when formulating MAS problems. While radar is used in [70] and electro-optical and infrared sensors are investigated in York, cameras are used in works such as [50], [63], [71], [72], and [73] According to Sun et al. [74], search sensors on unmanned aerial vehicles (UAVs) are downward-facing cameras. The video footage is delivered to a ground station for post-processing to identify targets. The UAV's motion planning, which includes navigation, guidance and control, is independent of the target detection or search procedure. Furthermore, as [75] shows, camera-mounted

UAVs are used for automated fault identification in massive constructions, including bridges. Variables like orientation (downward or forward facing), spectrum, clarity of image, and spatiotemporal variations of image quality significantly influence how the problem is phrased and how the search strategy is executed, even in the context of camera-based sensors in multi-robot search problems. In this paper, we investigate the use of downward-facing cameras as search sensors, considering their unique characteristics that impact the multi-agent search strategy's target detection capability. To make it easier to apply MAS techniques in practice, the search area is frequently partitioned into small cells, frequently in a gridded manner. Nonetheless, there are two possible ways to implement the decision-making process: a continuous space or a gridded space. This is particularly true when deciding the best course for the search agents. Two primary subtasks of a thorough search strategy are search (target identification) and agent path planning.

To minimize search time and maximize a predefined effectiveness parameter, like the rate of information gain, the search's effectiveness must be considered at every stage of path planning. Many scholars often prefer to represent the search space with a grid, drawing on techniques from dynamic computing, graph-based search concepts, strategy theory, and team theory. This requires making choices for the agent's next best cell to move into. Nonetheless, there are few outliers, such as in the works of [56], [57], and [58] where the decision-making process is carried out in a continuous area. The authors use ideas from locational optimisation issues in continuous spaces in these situations.

The search aspect of the task, which entails target identification using onboard search sensors, is an essential component of the MAS strategy. Creating and resolving MAS problems heavily depends on the sensors' spatial search efficiency, also known as the sensor footprint. Figure 1 displays multiple sensor footprints frequently employed in the MAS literature. Any area covered by the searching sensor in Figure 1(a) is inspected, indicating that the target has been recognized, provided it is present and within the camera's range. The sensor footprint is typically handled as a single cell, though occasionally, it may cover several gridded cells. When the sensor footprint extends over multiple cells, the path planning problem resembles an exhaustive search problem ([18]) or an area coverage problem ([76]). Most MAS literature uses a sensor footprint similar to Figure 1(a), where target detection requires more than one scan over a cell. Exponentially decreasing sensor efficacy models have been utilized in several investigations in the literature, such as those by [56], [57], [58], and [77]. Continual or discrete (gridded) space can be used to plan a search agent's next move based on each task's specific problem formulation and solution.

The performance of distributed quadcopter systems in multi-agent search relies heavily on sensor efficacy [78]. Instead of extending sensor ranges, one study suggests modeling neighbouring agents' intentions for better performance. Effective coordination and communication among

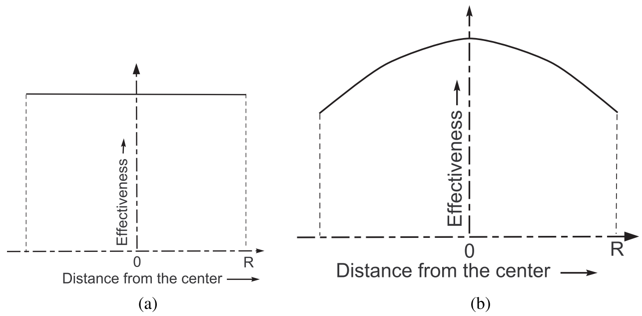

FIGURE 1. Sensor footprints adopted generally in the literature sensor types: (a) straight and (b) non-straight footprint.

quadcopters are crucial, and strategies for merging occupancy probabilities in multi-UAV cooperative search have been proposed [79]. Optimizing multi-agent search with varying sensor effectiveness in distributed quadcopter systems involves devising tactics to enhance search performance when sensors exhibit different detection probabilities. Research in this domain primarily focuses on decentralized methods, where each agent autonomously decides actions based on local data. Critical tactics for improving search performance include maximizing predicted information gain, consensus-based coordination, and intermittent information-driven search strategies [80]. Furthermore, a distributed search-planning framework allows agents to adapt their decisions dynamically while considering their peers' plans, utilizing model predictive control for cooperative search trajectories [39]. A decentralized approach for multi-target search employs a modified Particle Swarm Optimization algorithm, utilizing onboard sensors on a swarm of unmanned aerial vehicles [45]. Efforts to enhance search efficiency in scenarios with varying sensor effectiveness emphasize the necessity of decentralized approaches, where each agent operates independently based on local data. Tactics such as consensus-based coordination, optimizing predicted information gain, and intermittent information-driven search are crucial for improving search performance. Coordinated teams of independent agents employing decentralized intermittent information-driven search tactics aim to enhance information gain while maintaining scalability and resilience to agent failures by alternating between slow sensing phases and rapid displacement periods [81]. Consensus-based coordination facilitates effective group coordination without relying on a leader-follower hierarchy, enabling agents to achieve mission objectives by exchanging data solely with nearby peers. This approach, treating all sensor platforms equally, enhances the resilience and scalability of multi-agent search operations. Fundamental to this process is the maximization of predicted information gain for each searching agent, enabling more efficient exploration of the search area and extension of the overall search period [82]. Utilizing a group of UAVs for cooperative search missions targeting multiple mobile ground targets can significantly enhance effectiveness, accuracy, collaboration, adaptability, and resource efficiency. This vision-based method employs UAVs equipped with vision-based technologies to collaboratively detect and track various mobile ground targets. By leveraging the combined capabilities of multiple UAVs, this cooperative search approach aims to improve the efficacy of target search missions ([73], [83]). Utilizing multiple UAVs in cooperative search significantly reduces the time required for target detection through several key mechanisms. Collaborative efforts enable UAVs to cover larger areas simultaneously, thereby increasing the likelihood of promptly identifying targets. UAVs enhance search efficiency and accelerate target detection by exchanging data and coordinating search patterns. Real-time information sharing among UAVs optimizes search paths, enabling quicker adaptation to shifting target positions. Furthermore, distributing the workload among multiple UAVs allows for more targeted and productive search operations, ultimately reducing the time needed for target detection. In scenarios such as rapid assessment of earthquake-affected areas, cooperative coverage control involves a combination of fixed-wing UAVs for general scanning and quadcopters for detailed information extraction and victim localization. This approach demonstrates the effectiveness of collaborative distributed control in reducing environmental uncertainty and optimizing coverage efficiency in post-disaster scenarios. Studies involving simulation and experimental validation underscore the system's ability to swiftly and effectively assess disaster-stricken areas ([22], [46], [73], [84], and [85]).

Using quadcopter swarms for regional reconnaissance and target monitoring presents challenges in locating and monitoring targets in unexplored areas. In uncertain, dynamic, and partially observable environments, centralised global optimisation techniques are not achievable, leading agents to act independently based on their own beliefs of the world. Promoting collaboration amongst several decentralized agents can be challenging because improper coordination might lead to competitive behaviour. The system's performance may need increased sensor ranges, underscoring the difficulty of maximizing sensor and communication ranges for effective multi-agent search. The system's performance may suffer from extended sensor ranges, underscoring the difficulty of maximizing sensor and communication ranges for effective multi-agent search [86]. Effective search and surveillance missions require decentralized collaboration among several UAVs in uncertain and dynamic situations. The system's performance may need increased sensor ranges, underscoring the difficulty of maximizing sensor and communication ranges for effective multi-agent search [87]. The multi-agent search problem has been approached by several algorithms, including the Voronoi-based online source searching method, the distributed cooperative search algorithm, and the dynamic target surrounding technique. For unmanned aerial vehicles, a distributed cooperative search strategy based on a Voronoi diagram demonstrated its state-of-the-art nature in multi-agent search by outperforming greedy and random search methods in speed and robustness. Based on the particle swarm optimization algorithm, a unique search strategy for a swarm of quadcopter drones was used. Its application showed its usefulness, accuracy, and resilience, establishing it as a state-of-the-art approach for multi-agent search with distributed quadcopter systems ([86], [88], [89]). To verify search techniques and compare performance based on criteria such as camera search effectiveness models, sensor range, and robot count, simulation systems have been built [88]. The coordination of quadcopter systems strongly impacts the effectiveness of multi-agent search. For example, applying a behaviour-based algorithm for multi-quadcopter surveillance jobs showed efficiency and robustness in various tests, such as positioning errors and broadcast message loss. Due to their reliability, scalability, and versatility in many settings, distributed quadcopter systems are an excellent choice for open-space search and surveillance operations [88].

This paper contributes to the existing body of research in multi-agent systems (MAS) and multi-robot systems (MRS) for target search and exploration tasks by addressing several critical gaps. Unlike many referenced works, this paper focuses on the practical application of a multi-quadcopter system equipped with downward-facing cameras specifically tailored for exploring unknown environments. While previous studies have explored theoretical models or applications in controlled environments, this paper emphasizes real-world scenarios, such as disaster-stricken areas, where the challenges are more complex and demanding. One notable contribution of this paper is its consideration of uncertainty in target search tasks, which is often overlooked in existing literature. By representing the presence or absence of targets with a distribution of uncertainty, the paper acknowledges and addresses the inherent unpredictability of dynamic and unstructured environments, thus enhancing the robustness and reliability of MAS/MRS systems in practical applications. Furthermore, the paper explores the efficacy of downward-facing cameras for target detection and localization in MAS/MRS systems, which remains relatively under-explored in the existing literature. By leveraging the unique advantages of downward-facing cameras, such as wide-area coverage and real-time monitoring, the paper aims to optimize strategies for deployment in multi-agent search scenarios, thereby enhancing target search efficiency. Lastly, the paper emphasizes integrating novel control and optimization techniques into practical applications for target search tasks, an aspect often lacking in existing studies. By conducting simulations in realistic environments using ROS, MATLAB, and Gazebo, the paper seeks to validate and demonstrate the effectiveness of its proposed approach, ensuring its applicability and scalability in diverse real-world settings. Overall, this paper contributes to advancing the field of MAS/MRS by providing practical solutions for efficient target search and detection in complex environments.

III. PROBLEM STATEMENT

Current research in multi-agent search (MAS) strategies lacks a cohesive approach, with either generic or fixed-wing

UAVs dominating the focus. Despite increasing popularity, Quadcopter UAVs are underrepresented in autonomous multi-agent search scenarios. Downward-facing cameras, a cost-effective search sensor, receive limited attention, and assumptions about uniform search effectiveness across their frames prevail. Non-uniform sensor footprint models lack justification, and the predominant use of gridded space for path planning may result in non-smooth trajectories. This research article proposes a novel MAS strategy that uses quadcopters and downward-facing cameras to address these gaps, formulating the problem in continuous space. The emphasis is developing a realistic, non-uniform camera search effectiveness model through experimentation to bridge the theoretical-practical gap. The simulation platform's development further facilitates the proposed strategy's real-world applicability.

A multi-quadcopter system equipped with downward-facing cameras for searching unknown workspaces is presented in this paper. The challenge here is efficiently executing the task through proper cooperation and teamwork between the robots. The scenario is at par with the natural environment since the camera effectiveness is considered high at the centre and decreases as we proceed away from it. Such a system's primary goal is to locate specific targets; therefore, whether the targets are present or absent is represented by a distribution of uncertainty, which is 1 when the target of interest is absent and 0 when it is discovered. Since they provide a comparable physical experience, the simulations are run in the ROS environment using MATLAB and Gazebo.

IV. PROPOSED METHODOLOGY

In this section, we elaborate on the methodology employed in our study.

A. CAMERA

With the use of the current research, this section investigates specific camera attributes that are pertinent to the retrieval problem. The damage level that must be assessed or survivors needing immediate aid are typical examples of visually visible targets in various settings, including search and rescue operations in areas devastated by natural disasters. There are often two types of cameras on drones, including quadcopters: one that faces ahead and one that faces downward.

The area of interest and the detection probability can be related in an equation to express the sensor efficiency measure:

$$f(q) = p(q) \tag{1}$$

where, $q \in Q$ is point of interest in $Q \subset \mathbb{R}^2$, The search area, $p(q)$, is the probability of detection of the target of interest present at q. If we assume that the search sensor is anisotropic, then we have the following:

$$p(q) = f(r) \tag{2}$$

where, $r = \|C - q\|$, and $C \in Q$ is a point directly below the sensor. Most research on multi-agent search, as seen in studies like [32], [57], [77], and [90], often adopts a flat effectiveness function.

This model is valid only for scenarios where high-quality images are available, which is not true with real-world applications. An exponential function is used in [57] for a generic search sensor.

B. SIMULATION SETUP FOR THE PROPOSED SEARCH STRATEGY

In this section, we present an overview of the realistic simulation platform developed for the proposed search strategy in this work. The simulation involves multiple quadcopters equipped with downward-facing cameras serving as the search sensors.

1) A CENTRALIZED AND DECENTRALIZED ARCHITECTURE

The multi-quadcopter search strategy outlined in this proposal consists of various key components such as task sharing, deployment optimization, control and search strategy with high effectiveness value. In this section, we initiate our discourse by delving into the spatial distribution characteristics of these individual components and the overarching search strategy. Our observations are summarized as follows:

1) **Task Sharing:** The Voronoi partitiTaskg scheme divides the search space Q into Voronoi cells V_i based on the positions of search agents. Each quadcopter is assigned to search within its corresponding Voronoi cell. This spatial task partitioning is distributed within $\mathcal{G}_D$ as the shape of each cell depends on the positions of neighbouring quadcopters.
2) **Deployment Optimization** The centroidal Voronoi configuration is determined for each quadcopter, where the solution depends not only on the quadcopter's location but also on the positions of its neighbours in $\mathcal{G}_D$. Therefore, the optimal deployment configuration is spatially distributed within $\mathcal{G}_D$.
3) **Control** The control law for achieving the centroidal Voronoi configuration utilizes a gradient that is also spatially distributed within $\mathcal{G}_D$.
4) **Search Effectiveness** The search task involves gathering information within the corresponding Voronoi cells using downward-facing cameras, leading to uncertainty reduction. While the search task itself is decentralized due to spatial task partitioning, communicating updated uncertainty density distributions during deployment introduces spatial distribution. This communication can occur in two ways: centralized architecture with a central server storing and retrieving information or distributed communication among quadcopters, resulting in a spatially distributed system.

The methodology proposed in this work adopts a hybrid centralized-decentralized approach in which the initial three components, explained above, employ a distributed architecture. In contrast, the final one opts for a centralized architecture for convenience, although a distributed architecture is also theoretically feasible. This hybrid nature is very essential and influential in real-time scenarios. In this configuration, a central server stores the updated uncertainty density and target detection probability distribution, furnishing this information to quadcopters upon request for centroid computation and density updates following search operations.

Individual controllers can work independently, depending only on information about the positions of nearby quadcopters, to compute Voronoi cells and their centroids using the uncertainty density from the central server and then derive the control law. Distributed communication amongst the quadcopters facilitates the capture of locational information. Nevertheless, when a central server is deployed to record uncertainty density, leveraging its capabilities to compute Voronoi cells and their centroids is pragmatic. When every quadcopter controller knows where the centroid of its own Voronoi cell is, it can compute the control law on its own. As such, a centralized architecture can calculate optimal deployment configurations (centroids) and spatial partitioning (Voronoi cells). A decentralized architecture for calculating the control law, guaranteeing optimal deployment (CVC), and carrying out the search task (updating the target probability density and uncertainty density) can come after this.

In the context of the proposed multi-quadcopter search strategy, the target point for each quadcopter is the centroid of its corresponding Voronoi cell, as provided by the central controller (implemented in MATLAB). Using a PID control law, the quadcopter is navigated towards the Voronoi cell centroid. The control algorithm is given as a pseudo-code in Algorithm 1.

Algorithm 1 Control Algorithm for Individual AR Drones

```
procedure ControlAlgorithm
    Transmit current state.
    Retrieve Voronoi cell and centroid from a central controller (MATLAB).
    Navigate towards the centroid.
    while not within proximity of the centroid do
        GOTO Step 1.
    end while
    Update uncertainty density and broadcast the updated information.
    while average uncertainty density surpasses a predefined threshold do
        GOTO Step 1.
    end while
end procedure
```

C. SIMULATION ENVIRONMENT

An environment generated using MATLAB and ROS/Gazebo platforms simulates the proposed methodology. An illustrative block diagram showing the implementation is in figure 2. The central control algorithm is programmed in MATLAB, and the later part is in the ROS environment. In this architecture, the density function updates and the calculation of centroidal Voronoi values are done by a single Matlab program. The computation of Voronoi cells is based on the current configuration of the multi-quadcopter system, retrieved from the ROS topics $/ardrone_i/ground_truth/state$. Data such as position, quadcopter orientations, uncertainty density updates, etc., is simulated using ROS topics.

1) CONTROLLER IMPLEMENTATION FOR ARDRONE

This paper selects ARDrone since it is one of the most popular quadcopters. This drone's properties are available as Unified Robot Description Format in the Gazebo simulation environment. In addition, ROS monitors all aspects of the quadcopter state, such as position, attitude, camera attitude, etc., via a transformed library [91]. The $/ardrone_autonomy$ package, developed by Mani Monajjemi and other contributors at the Autonomy Laboratory, Simon Fraser University, is utilized for simulation control. This will enable the drone control not only in simulation but also in actual physical implementation. Motion control of the ARDrone is realized by publishing to the $/cmd_vel$ topic, equivalent to providing the desired velocity to the quadcopter.

2) MULTI-UAV CONTROL

In our implementation, we employ a complex transform tree structure to accommodate multiple quadcopters with individual UAVs designated with a namespace(Example: $/ardrone_1$). Distinct ROS topics are created using these namespaces, which are then used to coordinate the individual UAV states and controllers. An example can be topics such as $/ardrone_1/ground_truth/state$, $/ardrone_1/cmd_vel$, and $/ardrone_1/bottom/image_raw$ which represents state, velocity, command input, and raw image data for the 'ARDrone 1' UAV. There will be as many topics as the number of UAVs in the system facilitating their control and coordination. While a UAV's state is a 6-dimensional vector, encompassing position and orientation, our implementation considers only the x and y positions (P_x and P_y), maintaining a constant altitude for horizontal flight. Each quadcopter adheres to Algorithm 1. This implementation achieves a genuinely hybrid control paradigm within the simulation environment.

3) QUADCOPTER CONTROL IN GAZEBO

The Voronoi partitioning and the computation of cell centroids are done by Matlab node in the form of $/centroid_i$ topics. The controller subscribes to these topic values and subsequently publishes the requisite velocity to the $/cmdvel$ topic specific to the corresponding ARDrone, which results in the drone's motion towards the Voronoi cell centroid. The position values the ARDrone quadcopter relays through

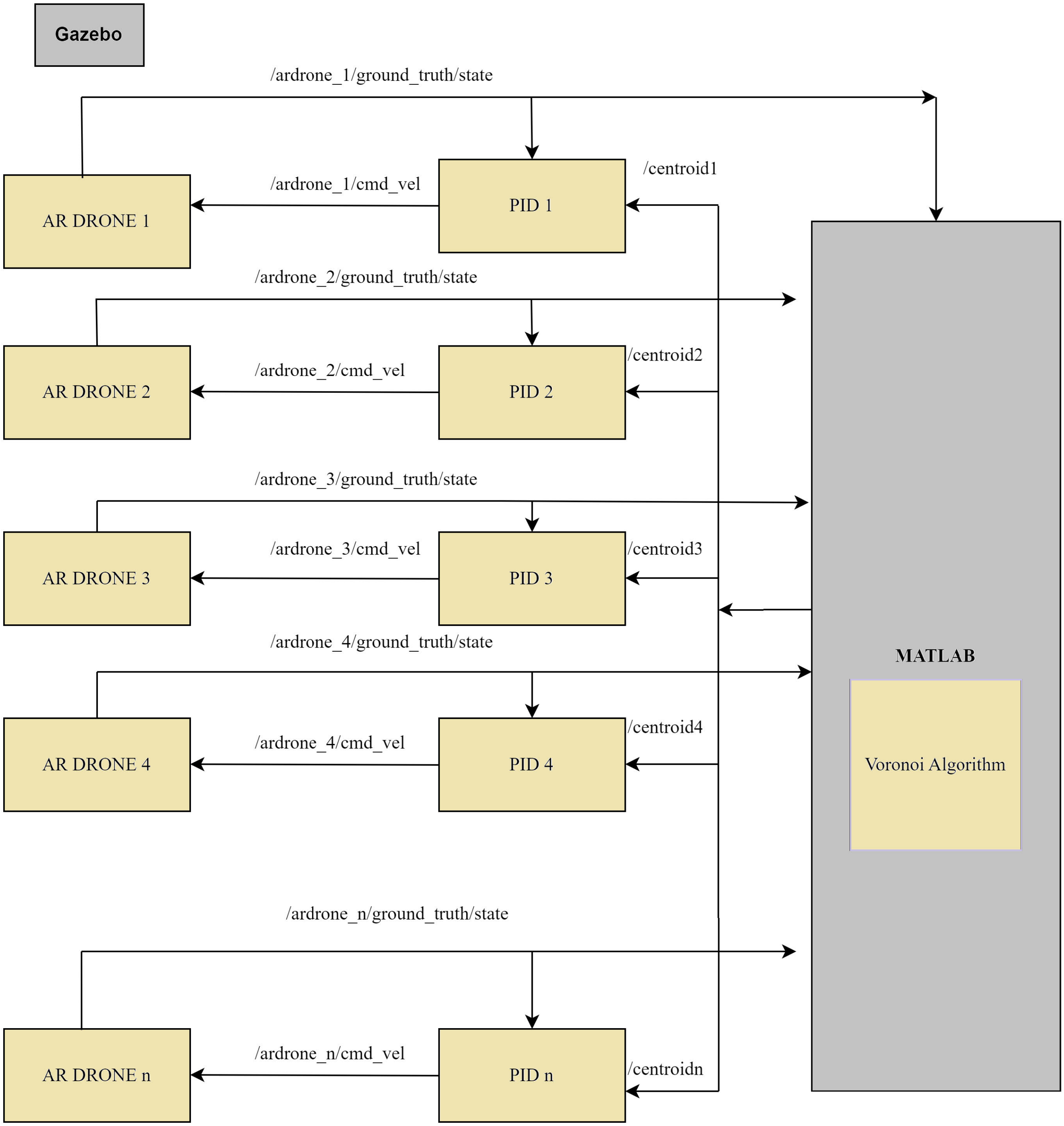

FIGURE 2. Simulation Environment for visualising the multi-quadcopter deployment in MATLAB and ROS environment.

the */groundtruth/state* topic is harnessed by the controller, interpreting the UAV's velocities as tilt angles.

Remark 1: The described simulation format offers two primary advantages. Firstly, it achieves a higher realism level than simulations conducted in environments like Matlab, where point mass models are often assumed for search agents (quadcopters). In the ROS/Gazebo simulation, the dynamics of the quadcopters are considered, providing a more accurate representation of their behaviour. It's essential to note that claims about the successful deployment of search agents into the CVC, as demonstrated in previous works such as [57] and [58], hold only when the search agents are assumed to be point masses. Secondly, the programs developed within the ROS/Gazebo environment for controlling quadcopters

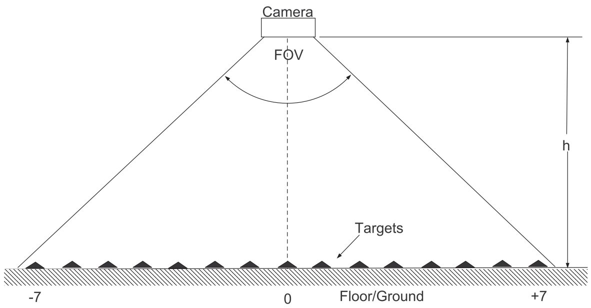

FIGURE 3. Experimental set up: Schematic representation. An experimental setup leveraging object identification to evaluate the camera's search effectiveness.

during simulation have the potential for direct application to physical quadcopters. This compatibility highlights the practical utility of the simulation, as control strategies developed and tested in the simulated environment can be seamlessly transferred to real-world quadcopters. This contributes to bridging the gap between theoretical concepts explored in simulation and their implementation in actual scenarios. We assert that the simulation platform is 'realistic' in this sense.

V. RESULTS AND DISCUSSIONS

This section presents the simulation and experimental results, comprehensively analysing the proposed search strategy. The simulation outcomes provide insights into the strategy's performance under controlled conditions, considering realistic dynamics and environmental factors. Subsequently, experimental results from real-world implementations further validate the strategy's efficacy and practical applicability. These findings thoroughly evaluate the proposed approach across simulation and physical experiments.

A. EXPERIMENTAL SETUP: CAMERA

Initial experiments were conducted to validate the search effectiveness of the down-ward facing camera, as shown in figure 3. A CMOS web camera is mounted at h above the floor. The camera featured a maximum resolution of 1600 × 1200 pixels, a frame rate of 30 fps, and a fixed focal length with a minimum focusing distance of 0.05 m. An isotropic camera is assumed. Markers of various shapes are positioned below at different distances from the camera's centre. A lower resolution of 640 × 480 pixels was selected for practical scenarios where high-resolution images are challenging to obtain due to the UAV altitude and environmental complexities. Once the setup is ready, various images are captured, and target identification is done via image processing. Successful detections are recorded to calculate the target detection probability. Target locations are denoted as $-7, \ldots, 0, \ldots, 7$, with 0 representing the target directly below the camera.

ArUco markers and triangular shapes are used as targets. The ArUco module is based on the ArUco library, a well-accepted and extensively used library for detecting square fiducial markers [92], [93]. An example of an ArUco marker used in our experiments is illustrated in Figure 4. ArUco markers, binary square fiducial markers, are crafted explicitly for straightforward and distinctive identification, even amidst noisy conditions. The detection process encompasses thresholding, contour filtering, bits extraction, marker identification, and corner refinement. ArUco markers prove highly effective in real-world scenarios, ensuring a generally high detection probability. Additionally, we incorporated triangular objects for target detection, relying on corner detection techniques. It's crucial to acknowledge that the detection probability for triangular objects is more susceptible to interference from noise.

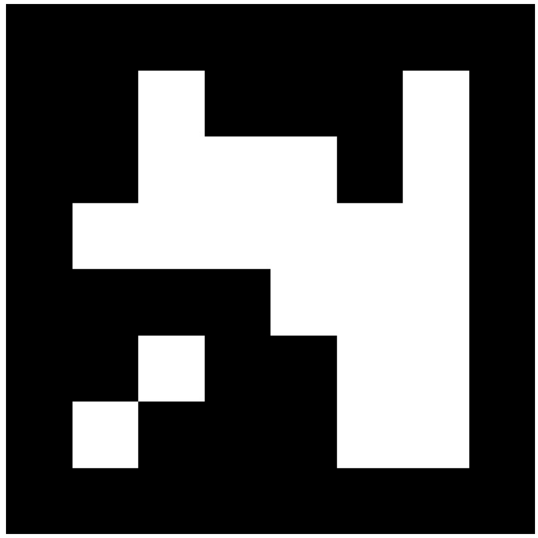

FIGURE 4. An ArUco marker used as a target in the experimental setup.

1) EXPERIMENTS WITH MARKERS

In the experiments, we utilized ArUco markers of dimensions 4 × 4 cm and 5 × 5 cm (figure 5). The captured images, taken against a plain floor background, were intentionally kept nearly noiseless. However, we introduced noise into the image space to simulate real-world scenarios with a mosaic or noisy background. This approach aimed to replicate conditions where background complexities might affect target detection.

The probability of detection of the 4 × 4 cm ArUco markers concerning relative distance from the camera centre is given in table1. The table shows the target detection probability of 4 × 4 ArUco markers based on their position relative to the central pixel in the image frame. The total number of detection attempts is 2000. The second column provides the number of successful target detection, and the third column provides the target detection probability. Position 0 represents a point directly below the camera. Figure 6 shows the best fit exponential curve and the plot of the target identification probability with the distance from the central pixel. The

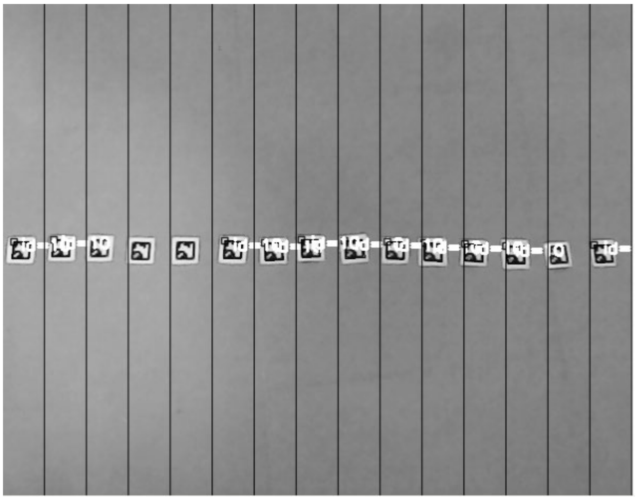

FIGURE 5. Experimental setup for target detection using 4 × 4 cm ArUco markers.

TABLE 1. Probability of target detection using 4 × 4 cm ArUco markers based on their position relative to the central pixel in the image frame. The second column provides the number of successful target detection, and the third column provides the target detection probability. Position 0 represents a point directly below the camera.

Location	Number of times target is detected	Detection Probability
0	1487	0.5199
1	1217	0.4255
2	1180	0.4126
3	1045	0.3654
4	233	0.0815
5	152	0.0531
6	131	0.0458
7	47	0.0164

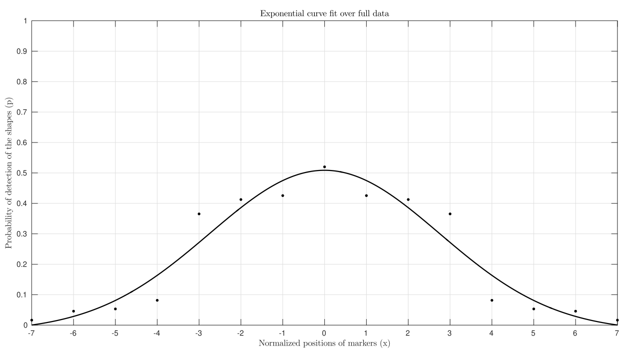

FIGURE 6. Best-fit exponential curve over the entire dataset for 4 × 4 cm ArUco markers' target detection probability for the data given in table 1.

exponential function used is:

$$f(x) = k \exp(-\alpha r^2) \tag{3}$$

where, r is the distance from the central pixel, $f(\cdot)$ is the probability of the target detection, and k and α are the parameters.

Salt and pepper noise, with salt probability 0.9 and pepper probability 0.1, has been incorporated to enhance the realism of the results. The experimental scenario is depicted in figure 7. The probability of detection is outlined in table 2, with the corresponding best-fit curve depicted in figure 8. The fitness metrics for this curve are as follows: SSE (Sum of Squares due to Error) = 9.7061; R-square (coefficient of

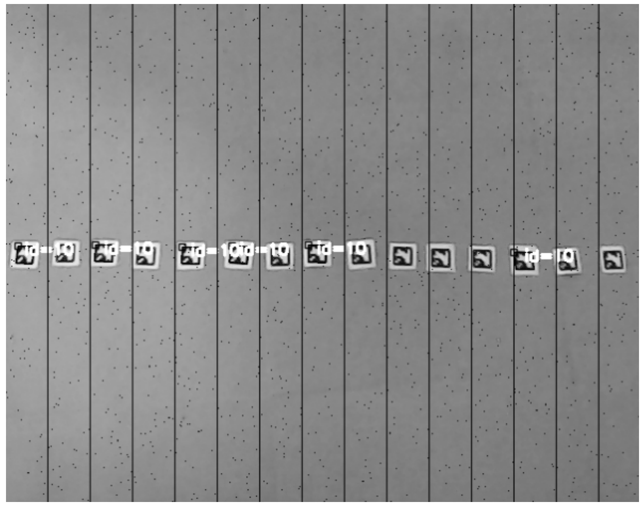

FIGURE 7. Experimental setup for target detection using 4 × 4 cm ArUco markers with added salt-and-pepper noise to simulate a mosaic/noisy background.

TABLE 2. Table showing the target detection probability of 4 × 4 ArUco markers with added salt-and-pepper noise based on their position relative to the central pixel in the image frame. The position 0 represents a point directly below the camera.

Location	Number of times target is detected	Detection Probability
0	493	0.1724
1	391	0.1367
2	374	0.1308
3	359	0.1255
4	291	0.1017
5	269	0.0941
6	213	0.0745
7	180	0.0629

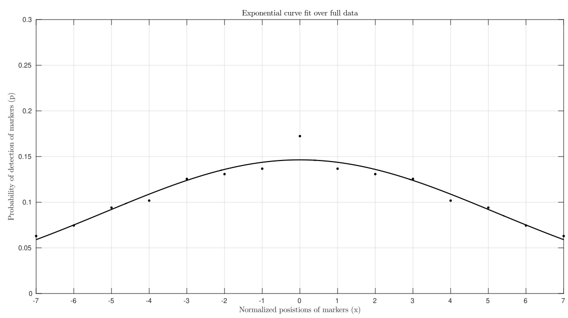

FIGURE 8. Probability of detection utilizing 4 × 4 ArUco markers with salt and pepper noise for the data given in table 2. The fitness metrics for this curve are SSE = 9.7061; R-square = 0.9317; Adj R-Sq = 0.9264 and RMSE = 0.0086.

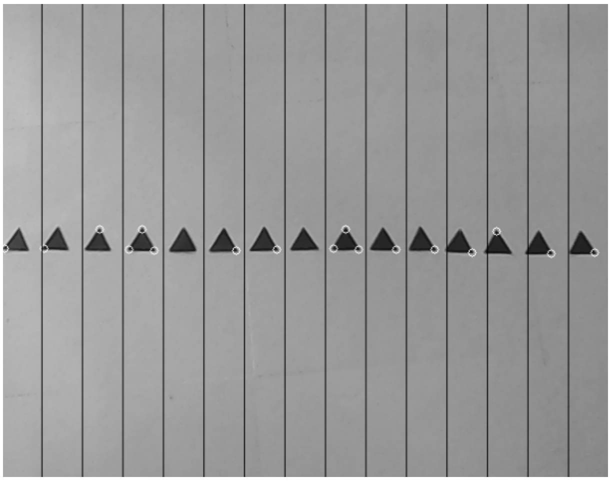

FIGURE 9. Schematic of the experimental scenario using triangular-shaped targets.

determination) = 0.9317; Adj R-Sq (adjusted R-square) = 0.9264; RMSE (Root Mean Square Error) = 0.0086.

2) EXPERIMENTS WITH TRIANGULAR TARGETS

As stated above, we have conducted experiments with triangular-shaped targets. The experimental scenario is shown in figure 10. The probability of detection is given in table 3 and the best-fit curve for the same is given in figure 10. The corresponding curve fitness metrics are SSE = 0.0011; R-square = 0.9880; Adj R-Sq = 0.9870 and RMSE = 0.0095 respectively. It is evident from the results that the detection probability and the effect of noise in the case of triangular markers are less than (5×5) ArUco markers since the probability curve is flatter. Compared with the results obtained with the ArUco markers, we can observe that the target detection probability distribution curve with the triangular targets is relatively flatter than that obtained with ArUco markers. The triangular shape has the least maximum target detection probability, while a 5×5 ArUco marker has the highest. However, the effect of noise on the fitness of target detection probability is most prominent with the 5×5 ArUco markers. These observations are interesting and can be generalized with more experiments with different kinds of targets and noise levels.

The information regarding the target detection probability and its position relative to the search sensor (camera) is a concern in various surveillance and path-planning applications. It is the main objective of this research. The efficiency of a surveillance quadcopter system (single or multi) depends on various factors such as target characteristics, algorithms used, camera characteristics, altitude of the quadcopter and so on. Even though implementing a generalized and universally implementable surveillance system is impossible, We have tried our best to accommodate all these constraints in the experimental setup to obtain a real-world performance. It is observed that the target detection efficiency is at its maximum under the camera and decreases uniformly away from it. Also, it is inferred that the target detection probability or the confidence level of the sensor efficiency for target detection inside its field of view can be modelled using a generalized exponential function given in equation 3

The main goal of the aforementioned experiments is to determine the typical variation of the probability of target detection concerning the camera's center of mass. This information can then be utilized to plan the deployment and path and the search tactics for either a single or multiple quadcopter search utilizing these cameras. The experimental results do, however, show that the likelihood of detecting a target is highest when it is right underneath the camera and falls monotonically as the target moves away from the center of the image.It was also noted that a curve over the target detection probability data may be fitted with an exponential function.

TABLE 3. Experimental results for the probability of target detection with triangular targets.

Location	Number of times target is detected	Detection Probability
0	1137	0.3976
1	1063	0.3717
2	1046	0.3657
3	926	0.3238
4	839	0.2934
5	656	0.2294
6	533	0.1864
7	471	0.1647

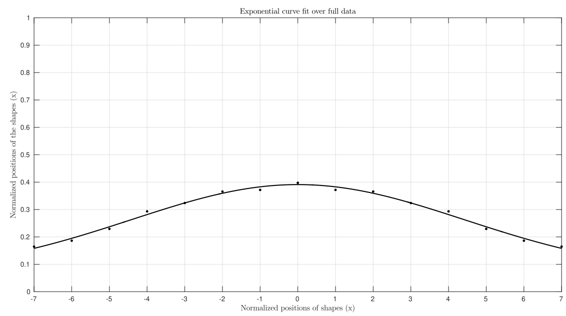

FIGURE 10. Exponential curve fit over the data for triangular target detection probability. The corresponding curve fitness metrics are SSE = 0.0011; R-square = 0.9880; Adj R-Sq = 0.9870 and RMSE = 0.0095 respectively.

B. SIMULATIONS IN ROS/MATLAB HYBRID PLATFORM

This section showcases the results of simulation experiments using Parrot AR Drone 2.0 quadcopter in ROS/Matlab hybrid simulation platform. The Gazebo platform is used since the drone's URDF model is available. All these will provide a close-to-real physical environment. Figure 11 illustrates the AR Drone 2.0 quadcopter within the Gazebo simulation platform.

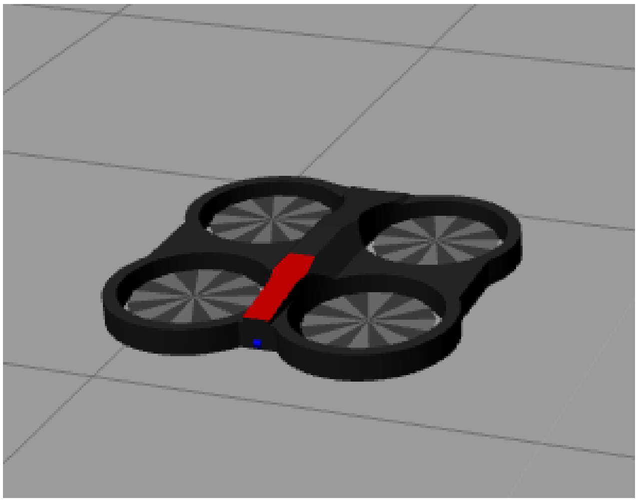

FIGURE 11. AR Drone model within the Gazebo environment.

The AR Drone 2.0 has robust features contributing to its versatile functionality. Its propulsion system, driven by brushless D.C. motors, incorporates a microcontroller that dynamically adjusts engine controls based on type and status. The LiPo battery, with a capacity of 1000mAh and 11.1V, undergoes continuous voltage monitoring to estimate battery life. The drone's motion sensors, including a 6-DOF inertial measurement unit, ultrasound telemeter, and pressure sensor, collectively enable automatic stabilization, altitude control, and speed measurement. A downward-facing camera and additional sensors, such as a 3-DOF magnetometer, enhance its sensing capabilities. Moreover, the AR Drone establishes its own Wi-Fi network, providing seamless wireless connectivity. These features make the AR Drone 2.0 well-suited for simulation experiments and real-world applications.

Multi Robot System: N Drones:

The simulation results illustrate the impact of the number of drones, denoted as N on search effectiveness (α). The system considers N values ranging from 5 to 45 quadcopters. Table 4 presents simulation times for a single iteration (t_{it}), overall simulation time (t_{tot}), and count of search instances (N_s) corresponding to varying numbers (N) of quadcopters. Observations reveal that both (t_{it}) and (t_{tot}) increase with N. In an ideally distributed scenario, this increment should be independent of N However, in a centralized architecture, time tends to increase with N. Moreover, when $N > 10$, the number of search iterations converges to 3. This convergence is attributed to the optimal deployment process, which involves computing Voronoi cells, their centroids, and moving quadcopters gradually towards these centroids, thus consuming time. It is to be summarized that the number of quadcopters increases t_{it} and t_{ot}.

1) EFFECT OF VARYING NUMBER OF DRONES(N) AND SENSOR RANGE

The search efficiency α, in terms of the number of iterative steps (deploy and search) required to explore the area of interest is studied. The various values for α(0.07, 0.1, 0.3, 0.5 and 1), and a constant $k = 0.6$ are considered in calculating the camera effectiveness model given in the equation 3. In tables 5 to 9, the total number of search steps required to complete the search, the number of iterations for each 'deployment' step, and the total simulation time for 3, 5, 15, 20, 30, 40, and 50 quadcopters performing the search with different α values is presented. A graphical representation of the same is also given in figures 12 to 16. From the tables and figures it can be inferred that as the number of quadcopters increases, the number of search steps decreases, coinciding with the logical perspective. The uncertainty decreases with an increase in N since the more drones there are, the more chance of target detection. The search steps can be lowered by using more number of quadcopters when performing a general search. However, as $N > 15$, there is not much variation in the computation time since the area of interest becomes too crowded by the number of quadcopters, which generally does not occur in practical scenarios.

A consolidated graphical representation of the same is given in figure 17. The number of search steps initially reduces and settles to a constant value even though the number of drones are increasing provided the α value remains constant. It becomes more prominent above 15 drones. This is due to the fact that as the number of drones (N) increases, the search space also grows larger. Initially, increasing the number of drones may lead to more efficient search as there

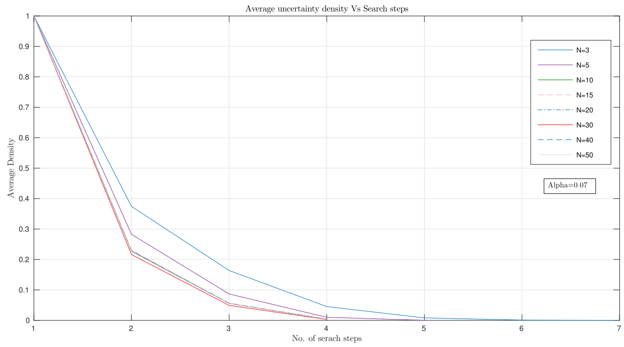

FIGURE 12. Variation in target detection uncertainty with $\alpha = 0.07$ and varying N.

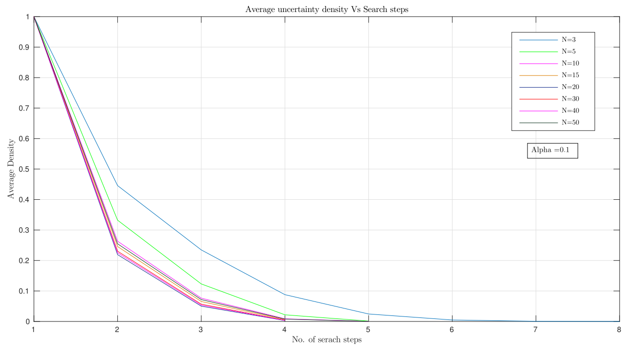

FIGURE 13. Variation in average target detection uncertainty with $\alpha = 0.1$ and varying N.

TABLE 4. Simulation times for a single iteration (t_{it}), overall simulation time (t_{tot}), and count of search instances (N_s) are depicted in correlation with varying numbers (N) of quadcopters. The number of quadcopters increases t_{it} and t_{ot}.

N	5	10	15	20	25	30	35	40	45
$t_{it(s)}$	0.9	1.1	1.3	1.5	1.7	2.0	2.3	2.5	2.6
$t_{tot}(s)$	53.0	51.6	128.1	115.4	151.7	167.2	321.3	352.5	383.7
N_s	6	3	3	3	3	3	3	3	3

TABLE 5. The number of deploy and search cycles required and the computation time taken for each iteration for an *alpha* value of 0.07.

N	Search Steps	Deployment iterations	Time for simulation(s)
3	6	10, 1, 1, 19, 3, 3	13.39
5	5	14, 1, 1, 13, 2	12.59
10	5	17, 1, 1, 6, 11	25.94
15	4	20, 1, 23, 2	85.22
20	4	36, 1, 13, 2	93.26
30	4	30, 1, 12, 3	124.68
40	4	26,1, 21,3	223.38
50	4	27, 2, 3, 4	298.57

TABLE 6. The number of deploy and search cycles required and the computation time for each iteration for an *alpha* value of 0.1.

N	Search Steps	Deployment iterations	Total simulation time(s)
3	8	11, 1, 1, 16, 3, 3, 3, 3	25.25
5	5	16, 1, 1, 11, 2	32.37
10	5	23, 1, 14, 3, 4	53.96
15	4	39, 2, 5, 8	70.86
20	5	25, 1, 20, 1, 17	161.96
30	5	26, 2, 13, 4, 5	163.46
40	4	23, 22, 1, 2	212.97
50	4	35, 1, 12, 2	250.5

are more agents exploring the space. However, once a certain threshold is reached, further increases in the number of drones may not significantly improve search efficiency because the search space may already be sufficiently explored. Another reason is as the number of drones increases, resource constraints such as computational power become more pronounced. These limitations could restrict the ability of the system to effectively coordinate a larger number of drones, leading to diminishing returns in search efficiency. Also, an increase in α represents a reduced imaging sensor range, and more quadcopters are required to saturate the workspace with their sensor footprint.

2) EFFECT OF α AND N ON TARGET DETECTION UNCERTAINTY

The uncertainty density function for varying values of $\alpha = 0.07, 0.3$ and 1 across different numbers of drones (N) has been computed and presented in figures 18, 19 and 20 respectively. Each trough in these plots signifies the level of uncertainty associated with the search efficiency of a UAV within the system. Notably, it's evident that lower uncertainty levels correlate with higher search efficiency. Upon closer examination, it becomes apparent that as the number of drones within the system increases, the uncertainty density decreases. This observation suggests that a greater number of drones leads to a more efficient search process, as evidenced

TABLE 7. The number of deploy and search cycles required and the computation time taken for each iteration for an *alpha* value of 0.3.

N	Search Steps	Deployment steps	Total Deployment time(sec)
3	14	10, 1, 1, 1, 15, 3, 3, 3, 3, 4, 4, 2, 1, 1	19.16
5	9	14, 1, 6, 9, 3, 2, 5, 3, 3	18.79
10	7	26, 16, 4, 5, 3, 3, 12	39.75
15	6	24, 14, 7, 4, 6, 12	52.92
20	6	27, 22, 1, 13, 12, 3	84.7
30	6	24, 21, 1, 10, 4, 18	112.68
40	5	35, 8, 2, 17, 3, 16	155.63
50	6	27,24, 2, 12, 4, 16	198.76

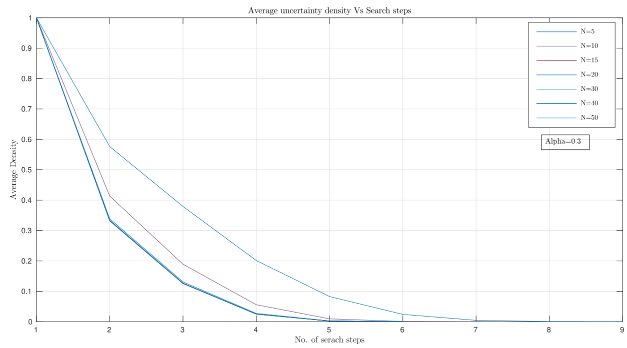

FIGURE 14. Variation in average target detection uncertainty with $\alpha = 0.3$ and varying N.

TABLE 8. The number of deploy and search cycles required and the computation time taken for each iteration for an *alpha* value of 0.5.

N	Search Steps	Deployment steps	Total Deployment time(sec)
3	20	12, 1, 1, 1, 1, 1, 11, 4, 3, 2, 2, 3, 3, 3, 3, 3, 1, 1, 1, 1	41.86
5	13	18, 1, 1, 1, 9, 2, 2, 2, 3, 6, 4, 8, 3	51.41
10	9	29, 15, 1, 8, 3, 7, 9, 5, 4	110.9
15	8	23, 12, 1, 19, 6,10, 2, 1	106.4
20	7	36, 7, 9, 18, 8, 12, 3	143.79
30	7	32, 16, 11, 3, 10, 21, 17	160.53
40	7	25, 21, 9, 6, 18, 20, 33	784.29
50	7	33, 6, 8, 7, 14, 27, 20	791

drones within the system increases, the uncertainty density decreases. This observation suggests that a greater number of drones leads to a more efficient search process, as evidenced

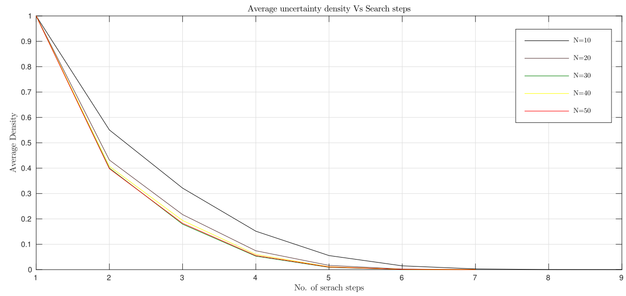

FIGURE 15. Variation in average target detection uncertainty with $\alpha = 0.5$ and varying N.

TABLE 9. The number of deploy and search cycles required and the computation time taken for each iteration for an *alpha* value of 1.

N	Search Steps	Deployment steps	Total Deployment time(sec)
3	36	10, 1, 1, 1, 1, 1, 1, 1, 1, 1, 12, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 7, 1	36.37
5	22	17, 1, 1, 1, 1, 11, 1, 1, 2, 1, 2, 2, 5, 6, 2, 6, 2, 3, 2, 2, 1, 1	32.93
10	13	28, 13, 2, 7, 6, 10, 4, 6, 6, 3, 15, 1, 1	62.27
15	11	29, 13, 8, 2, 8, 8, 2, 11, 2, 1, 1	69.02
20	10	39, 1, 17, 7, 6, 14, 3, 6, 2, 2	94.98
30	10	27, 14, 14, 7, 16, 15, 14, 8, 1, 26	204.88
40	10	25, 18, 8, 3, 8, 36, 10, 6, 15, 4	239.5

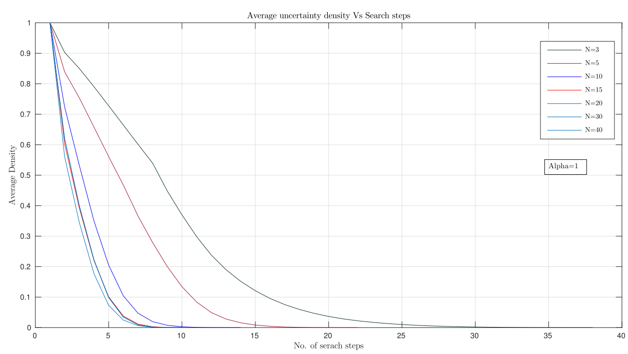

FIGURE 16. Variation in average target detection uncertainty with $\alpha = 1$ and varying N.

by the reduced uncertainty in target detection. Furthermore, a lower value of α appears to provide enhanced coverage and a notable reduction in target detection uncertainty.

These findings hold significant practical implications, particularly in scenarios where optimal resource allocation is crucial. By leveraging these results, it becomes feasible to determine the optimum number of UAVs equipped with similar imaging sensors required to effectively cover a given area of interest. This optimization process can

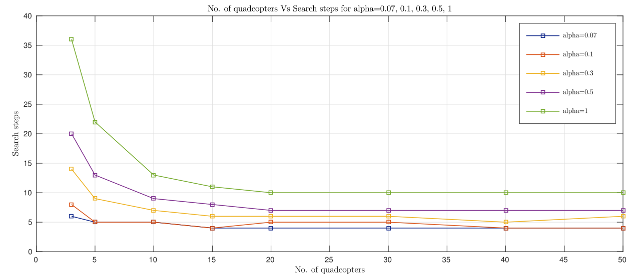

FIGURE 17. A consolidated graphical representation portraying the number of deploy and search cycles required as well as the computation time taken for each iteration for $\alpha = 0.07, 0.1, 0.3, 0.5, 1$ and $N = 3, 5, 10, 15, 20, 30, 40, 50$.

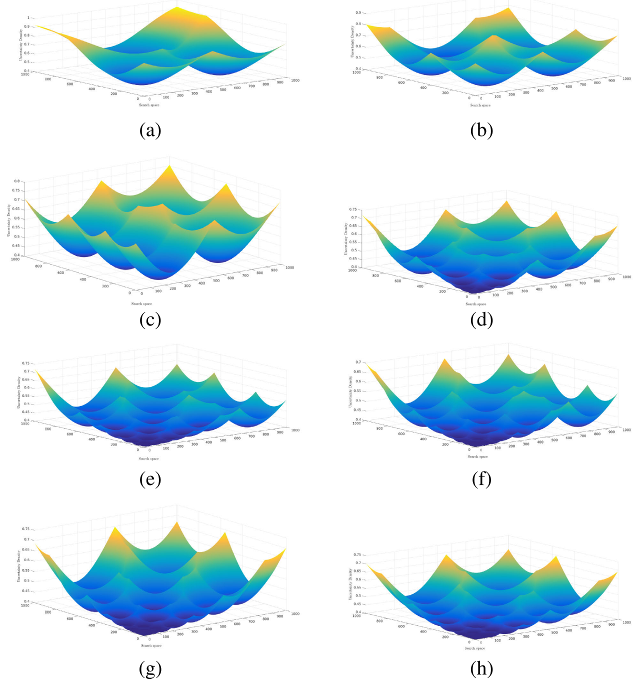

FIGURE 18. The uncertainty density function for various N values(increasing from figure (a) to (h)) for $\alpha = 0.07$.

lead to the efficient allocation of resources while ensuring comprehensive coverage and minimal uncertainty in target detection, thus maximizing the effectiveness of UAV-based surveillance and reconnaissance operations.

3) OPTIMAL DEPLOYMENT

The drone configuration at the end of the initial deployment and search phase with $\alpha = 0.07$ for various N values is depicted in figure 21. The centroidal Voronoi partitioning method is performed for the search space partitioning. The drones starts deployment process from a starting point(here it is leftmost bottom point). As individual drones calculate their respective centroidal Voronoi cells, the partition boundaries changes and the process terminates when all the drones reaches the centroids of their respective Voronoi cells. The readers can refer [94] for an in-depth analysis of centroidal

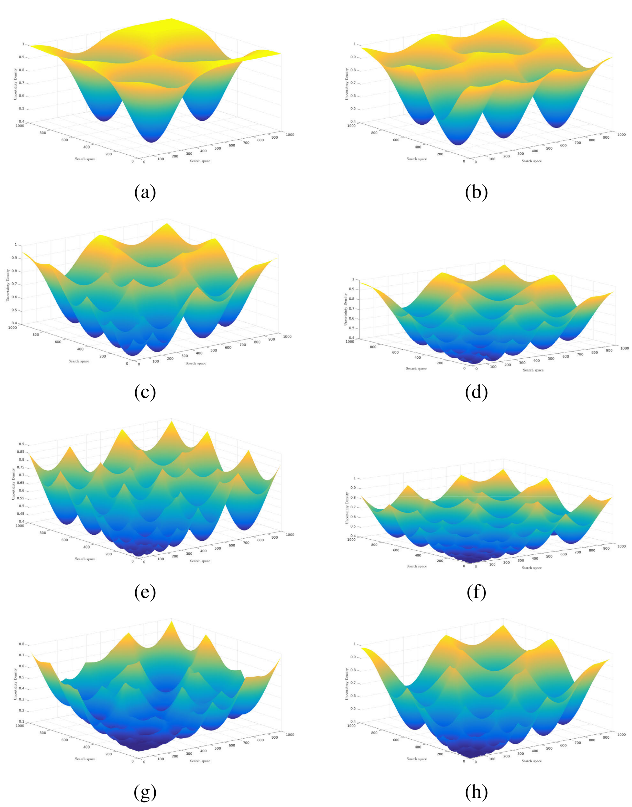

FIGURE 19. The uncertainty density function for various N values (increasing from figure (a) to (h)) for $\alpha = 0.3$.

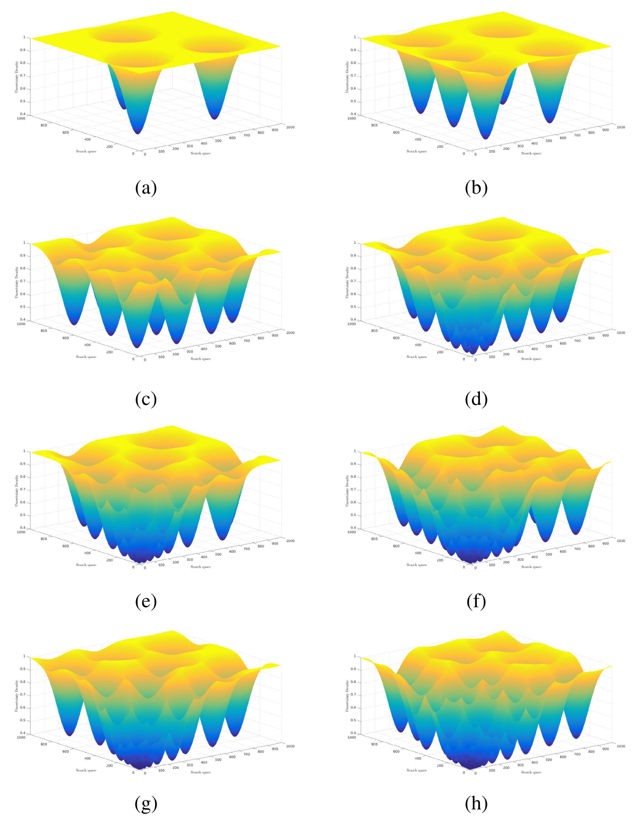

FIGURE 20. The uncertainty density function for various N values (increasing from figure (a) to (h)) for $\alpha = 1$.

Voronoi computation. It is observed that the optimality in area allocation degrades as the number of drones increases. The non-uniformity in deployment has implications for search performance. Lloyd's algorithm-based optimal deployment halts when quadcopters are close to their respective centroids by a predefined tolerance d_{tol}. It's important to mention that the exact value of d_{tol} has been used for all values of N in this scenario. Reducing this tolerance may be possible to achieve a more uniform deployment for scenarios with higher N. Also, an imaging sensor with large α) value is more effective in scenarios where N is larger.

C. SUMMARY OF THE RESEARCH CONTRIBUTIONS

This research addresses the intricate challenge of cooperative multi-agent search by focusing on the deployment of quadcopter UAVs equipped with downward-facing cameras. Several significant contributions distinguish this study. Firstly, it formulates a multi-agent search strategy utilizing quadcopter UAVs with downward-facing cameras and introduces a realistic search effectiveness model that accurately considers degradation away from the camera center, thereby improving model accuracy compared to existing literature. Secondly, the research presents a comprehensive approach to uncertainty reduction through the optimal deployment of quadcopters. This strategy leverages centroidal Voronoi configuration, demonstrating its effectiveness in maximizing uncertainty reduction and information gain. Additionally, the study explores the spatial variation of camera effectiveness within its image frame, leading to an in-depth analysis and the development of an experimental setup for obtaining a sensor effectiveness model. A hybrid centralized-decentralized architecture simulates the proposed multi-quadcopter search strategy using the ROS/Gazebo and Matlab-based platform, serving as a valuable tool for realistic experiments. This platform enables the validation and comparative study of the proposed approach under various parameters, presenting detailed experimental results, including establishing the search effectiveness model and the feasibility and efficiency of the proposed search strategy. Lastly, the versatility of the simulation platform is highlighted, supporting experiments with physical A.R. Drones, allowing for the evaluation of parameters such as the optimal number of quadcopters and the type of cameras. This research significantly advances multi-agent search strategies by providing valuable insights for practical applications and future research in autonomous search and reconnaissance missions. Its contributions lie in formulating an effective multi-agent search strategy, developing a realistic search effectiveness model, and creating a versatile simulation platform for experimentation and validation, ultimately enhancing the capabilities and understanding of distributed multi-robot systems for target search and exploration tasks.

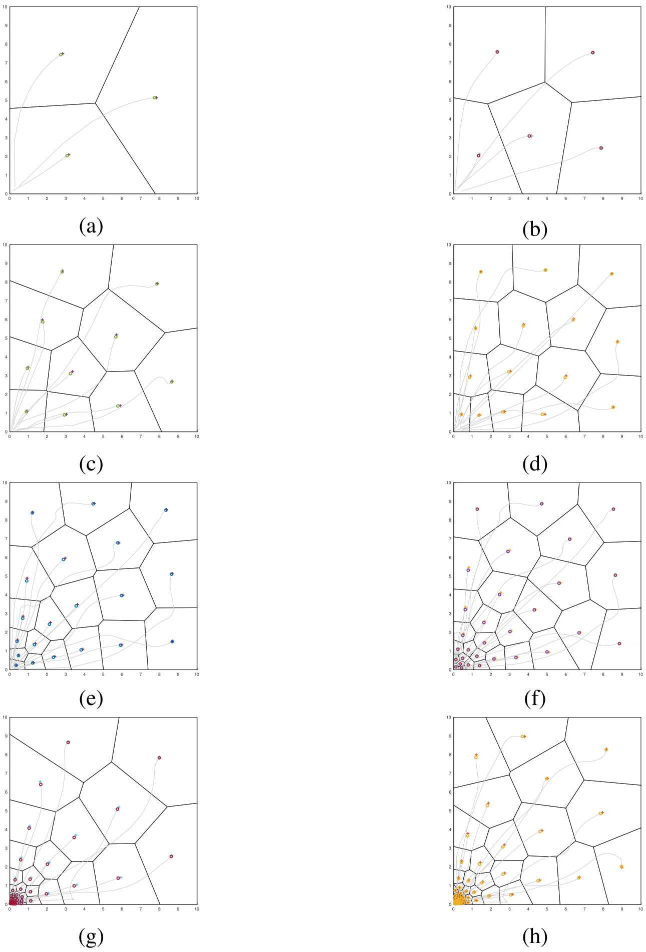

FIGURE 21. The drone configuration at the end of initial deploy and search phase with $\alpha = 0.07$ and $N = 3, 5, 10, 15, 20, 30, 40$, and 50.

VI. CONCLUSION AND FUTURE SCOPE

This paper addresses the intricate challenges of cooperative multi-agent search, focusing on formulating a strategy using quadcopter UAVs equipped with downward-facing cameras as search agents. Unlike conventional approaches, our strategy considers the practical degradation of search effectiveness away from the camera centre, introducing a more realistic model. The problem is framed as optimizing quadcopter deployment to maximize uncertainty reduction, with a 'deploy' and 'search' strategy based on centroidal Voronoi configuration. The study delves into the spatial variation of camera effectiveness for target detection. An experimental setup is devised to obtain a sensor effectiveness model by observing non-uniform effectiveness within the image frame. Target detection experiments establish an exponential function as a suitable model for spatial variation. A simulation platform is developed using ROS/Gazebo and Matlab, offering a valuable tool for realistic experiments to validate the proposed search strategy. Detailed results include experiments for obtaining the search effectiveness model and simulation experiments showcasing the platform's capability and the proposed strategy's performance under different parameters. The simulation experiments evaluate the impact of the number of search quadcopters and camera effectiveness parameters on the performance of the proposed multi-quadcopter search strategy. The hybrid centralized-decentralized architecture of the platform enables a comprehensive comparative study and parameter optimization for real-world missions. This work contributes to advancing multi-agent search strategies, offering practical insights and a versatile simulation platform for future research and applications in autonomous search and reconnaissance missions.

The study acknowledges limitations in relying solely on theoretical models and simulations, potentially leading to discrepancies with real-world performance. Simplifications in the model, like assuming uniform sensor effectiveness degradation, may oversimplify scenarios. Additionally, the narrow focus on downward-facing cameras overlooks other sensor modalities, and scalability to larger search areas remains unexplored. However, the developed simulation platform has potential for real-world experimentation, facilitating parameter optimization and offering a foundation for practical implementation. Future work can refine the strategy's applicability and address limitations by considering broader sensor modalities, improving scalability, and enhancing the simulation platform for more realistic scenarios.

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AUTHOR CONTRIBUTIONS

Jeane Marina D' Souza: idea generation, software simulation, initial writing. Vishnu G. Nair: review, formatting and editing, submitting. K. R. Guruprasad: overall supervision and review.

DECLARATIONS

FUNDING AND CONFLICTS OF INTERESTS/COMPETING INTERESTS

The authors declare that no competing financial interest or personal relationship could have appeared to influence the work reported in this paper. The authors have no relevant financial or non-financial interests to disclose.

AVAILABILITY OF DATA AND MATERIALS

The data supporting this study's findings are available from the corresponding author upon reasonable request.

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