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Autonomous Swarm Drones Exploration using Hybrid Frontier-Tracing and Ray-Casting Frontier Detection

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Abstract. Frontier-based exploration has become a fundamental paradigm in robotic navigation, where frontiers represent the dynamic boundary between known and unknown regions. The effectiveness of this approach depends heavily on the speed and accuracy of frontier detection, as faster detection not only accelerates the overall exploration process but also enhances decision-making quality through more up-to-date environmental information. In this paper, we propose a hybrid frontier detection method for autonomous swarm drone exploration that integrates the Frontier-Tracing Frontier Detection (FTFD) algorithm with a ray-casting strategy. The FTFD component exploits previously identified frontiers and scan endpoints to efficiently update new exploration targets, while ray casting provides accurate detection of boundaries in the drone's immediate surroundings. This integration is particularly suited for drones equipped with four directional sensors, thereby enabling full 360° situational awareness. Simulation results within a grid-based environment demonstrate the effectiveness of the proposed method in achieving efficient and scalable swarm exploration, validating its potential for real-world multi-agent navigation tasks.

Keywords: unknown environment, swarm drones exploration, ray casting, frontier tracing, frontier detection

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are aircraft systems engineered to function without an onboard human pilot. These platforms can be remotely controlled or programmed to operate autonomously through integrated electronic components, including sensors, microcontrollers, and communication modules [1]. UAVs are increasingly acknowledged for their versatility in executing a wide range of missions, from data acquisition to exploration, while reducing the necessity for direct human intervention. Their ability to operate effectively in hazardous or inaccessible environments renders them highly valuable for autonomous applications that would otherwise pose significant risks to human safety [2]. Since their inception, UAVs have profoundly transformed various industries by simplifying complex tasks, streamlining workflows, and enhancing operational efficiency. They have been extensively adopted for applications such as aerial photography, delivery services, environmental monitoring, disaster response, agriculture, weather forecasting, wildlife tracking, law enforcement, entertainment, and military operations [3]. In disaster scenarios, UAVs provide real-time aerial surveillance, assist in locating injured individuals, and demonstrate clear advantages over conventional methods such as helicopters or human search chains by offering faster, safer, and more precise responses [4]. Their integration with advanced technologies, including high-resolution cameras, sensors, and radar, further supports disaster victim identification (DVI) and enhances disaster management strategies [5]. Unlike larger aerial platforms, UAVs can access confined or hazardous areas and deliver detailed close-range visual data, offering critical capabilities unattainable through traditional approaches[3][6].

Micro Aerial Vehicles (MAVs), often termed small drones, are compact and lightweight aerial robots increasingly deployed across various domains. Their designs encompass multirotor, flapping-wing, fixed-wing, morphing, and hybrid configurations [7][8][9]. Among these, quadrotors have gained prominence due to their superior maneuverability, vertical take-off capability, and relatively simple design. Typically weighing around 100 grams or less and comparable in size to a human hand, MAVs are particularly suited for indoor exploration in hazardous environments[10][11]. Their small form factor and agility enable safe operation near humans, while their lightweight design minimizes risks of environmental or human damage in the event of a collision[12][9]. The compact size of MAVs imposes inherent limitations, including short flight endurance, restricted sensor range, and limited power capacity, rendering them unsuitable for large-scale tasks when operating individually [13]. These constraints have stimulated significant interest in swarm-based MAV systems, where collective cooperation enhances effectiveness, akin to social behaviors observed in biological systems [14][15]. Typically operating without GPS and designed for indoor environments, MAVs require alternative exploration and navigation strategies. Swarm robotics leverages distributed control, with each robot relying on local sensing and independent decision-making, while collaboration enables the team to achieve goals unattainable by a single unit. Such cooperation offers key advantages, including redundancy reduction, faster task execution through parallelization, and the capacity to perform complex missions collectively [16].

Micro Aerial Vehicles (MAVs) are essential for autonomous exploration, particularly in environments where prior information is unavailable. In such settings, robots must prioritize safety, navigate around obstacles, and optimize information gathering [17][18][19]. The challenges are compounded by MAVs' inherent limitations, such as limited power, computational capacity, memory, and the lack of GPS, which demand the use of lightweight and efficient algorithms for optimal area coverage [20][21] [22]. Frontier-Based Exploration (FBE) has become a leading strategy due to its ability to efficiently identify the boundaries between known and unknown areas, making it well-suited to the constraints of MAVs [23][24][25]. Various methods for detecting frontiers have been developed, such as Wavefront Frontier Detector (WFD), Fast Frontier Detection (FFD), Expanding-Wavefront Frontier Detection (EWFD), and Frontier-Tracing Frontier Detection (FTFD), with FTFD proving to be the most efficient[26][27][28][29]. To further improve swarm UAV exploration in complex environments, this study introduces a hybrid FBE method that combines FTFD with ray casting, offering a more adaptable and informative exploration framework (Caley et al., 2019)(Wang et al., 2024)..

2. Proposed Method

The proposed method integrates Frontier-Tracing Frontier Detection (FTFD) with ray-casting to enable efficient autonomous swarm drones exploration. At each time step t_1 range measurements from four orthogonally oriented sensors are used in a ray-casting process to identify candidate frontier endpoints. These candidates, together with existing frontier boundaries, are refined through FTFD to update the frontier set from F_{t-1} to F_t. Each drone then selects the nearest frontier and navigates toward it using a shortest-path strategy based on Breadth-First Search (BFS). Upon reaching a frontier, it is removed from the set, while unexplored frontiers remain available as future targets. In swarm deployment, this hybrid mechanism allows multiple agents to coordinate frontier allocation, minimize redundancy, and improve overall coverage efficiency under limited computational resources. **Figure 1** presents the results of frontier detection obtained through the ray-casting algorithm.

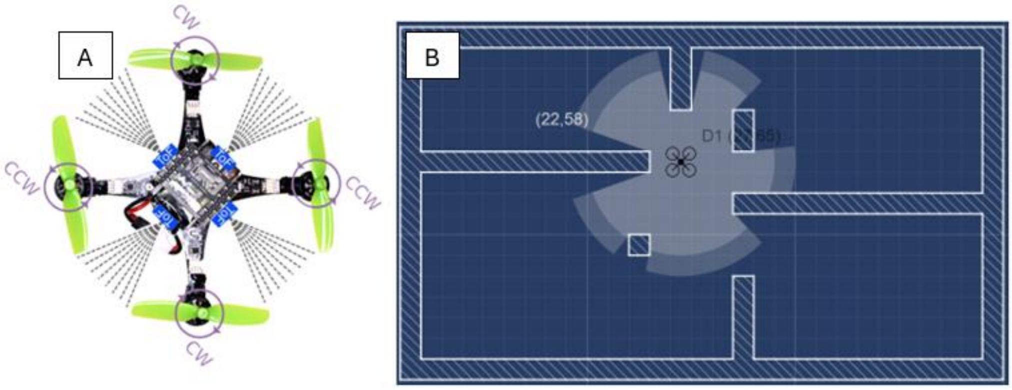

Figure 1(A) Representation of four ranging sensors facing forward, backward, left, and right on a drone; (B) Frontier Detection using Ray-Casting Algorithm

Algorithm: Hybrid Frontier-Tracing and Ray-Casting Frontier Detection
Input : Grid Map (unknown map with wall and obstacles) , Drones
Output : Explored map using Hybrid Frontier-Tracing and Ray-Casting Frontier Detection
Step 1 : initialization
Step 2 : Calculated must explored cells
Step 3 : Detect Frontiers for every drone using ray-casting algorithm
Step 4 : Update detected frontiers using FTFD
Step 5 : Drones go to their nearest frontiers using BFS
Step 6 : Remove visited frontier from frontier set and set free area
Step 7 : Repeat step 3 until no frontier remains in the frontier set.

The Hybrid Frontier-Tracing and Ray-Casting Frontier Detection algorithm is designed to optimize autonomous swarm drone exploration in unknown environments. In this approach, each drone maintains its own frontier set, ensuring independent exploration tasks and preventing inter-drone collisions. The Frontier-Tracing Frontier Detection (FTFD) algorithm plays a central role in improving the efficiency of frontier updates by employing a memoization technique, in which previously detected frontiers are retained in the frontier set until they are explicitly visited by a drone. This strategy reduces redundant computations and accelerates the overall exploration process. Complementing this, the ray-casting algorithm provides a realistic simulation of range-finder sensor behavior. Each drone is equipped with four sensors placed on its four sides, with each sensor covering a 45° field of view and a sensing range of approximately 3 meters, effectively

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achieving 360° environmental perception. Such a configuration can be practically realized using Time-of-Flight (ToF) sensors, enabling accurate detection of obstacles and exploration boundaries.

Algorithmically, the process begins with initialization of the grid map and swarm (Step 1), followed by calculating the total number of cells that must be explored (Step 2). Each drone then performs frontier detection using the ray-casting algorithm (Step 3), after which the detected frontiers are refined and updated through FTFD with memoization (Step 4). The drones navigate to their nearest frontier cells using a Breadth-First Search (BFS) path-planning strategy (Step 5). Once a frontier is reached, it is removed from the frontier set and the corresponding area is marked as explored (Step 6). These steps are iteratively repeated until no frontier remains in the frontier sets of all drones (Step 7), thereby ensuring complete and efficient exploration of the environment.

3. Result and Discussion

The simulation was implemented in the JavaFX framework within a 50 × 50 grid-based occupancy map (cell size: 10 pixels). A swarm of three drones, each equipped with a ray-casting sensor providing a 360° field of view and a 10-cell sensing radius, was deployed. The environment included walls and static obstacles to define navigable and restricted areas. Exploration was conducted by iteratively detecting and navigating toward frontiers, with each drone maintaining its own frontier allocation set to ensure coverage efficiency and collision avoidance.

The simulation results, as presented in **Figure 2**, were successfully implemented using the JavaFX framework within a 50 × 50 grid-cell workspace. A swarm consisting of three autonomous drones, each equipped with a sensor field of view (FOV) spanning 10 cells, was deployed to explore the environment. The experimental outcome indicated that a total of 2,057 cells were effectively explored during the mission. The proposed Hybrid Frontier-Tracing and Ray-Casting Frontier Detection approach demonstrated significant effectiveness: the Frontier-Tracing Frontier Detection (FTFD) component ensured continuous and efficient frontier updates, while the ray-casting algorithm provided accurate perception of the drones' surrounding environment. The integration of these two complementary methods enabled real-time visualization of dynamic frontier updates in parallel with environmental sensing. Collectively, these findings validate the robustness and applicability of the proposed hybrid strategy for autonomous swarm-based exploration tasks, particularly in complex and discretized environments.

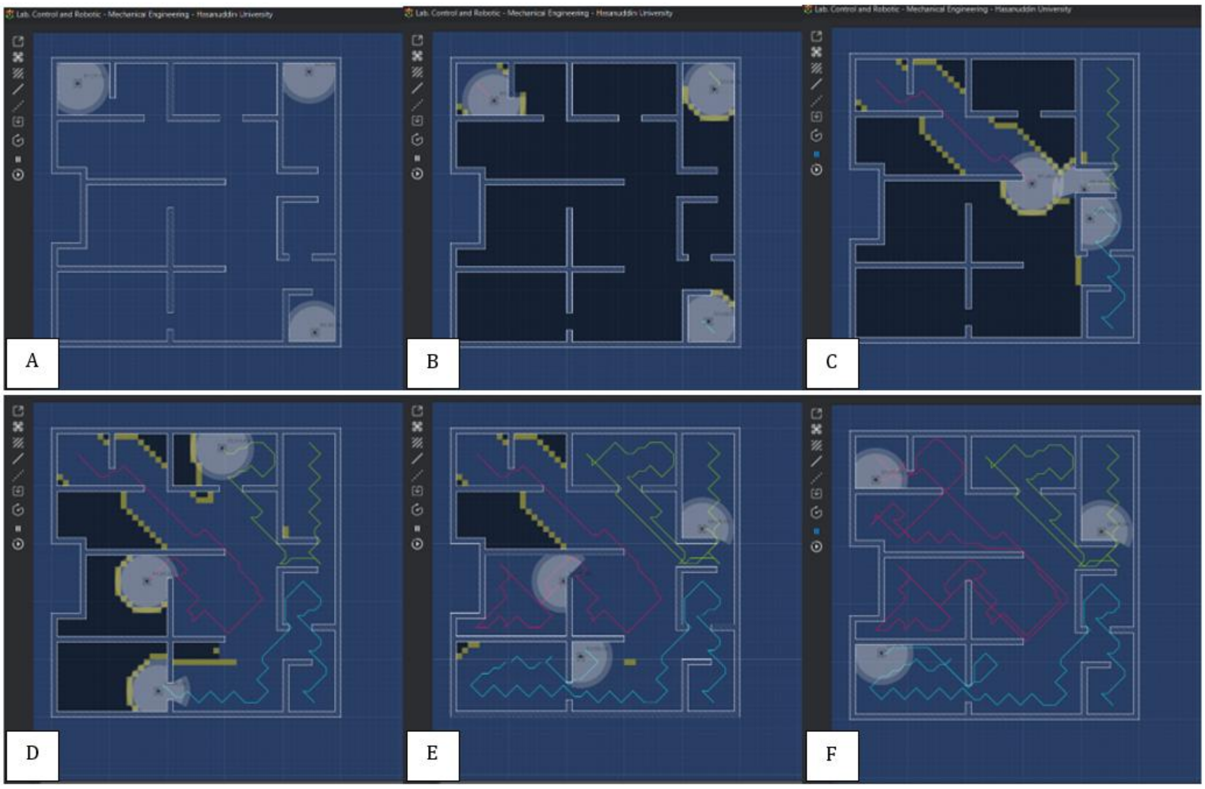

Figure 2 Simulation result with 50 x 50 grid cells

4. Conclusion

This study has introduced a hybrid frontier detection framework for autonomous swarm drone exploration, integrating the Frontier-Tracing Frontier Detection (FTFD) algorithm with the ray-casting method, and implemented within the JavaFX simulation environment. The ray-casting algorithm effectively modeled the sensing capabilities of drones by simulating multi-directional range detection, ensuring accurate environmental perception in a discretized grid map. To improve computational efficiency, memoization was incorporated into the FTFD algorithm, leveraging the recurrent intersection of new sensor data with previously identified frontiers to accelerate frontier updates. The simulation results demonstrated that the proposed hybrid strategy enabled the swarm of drones to achieve complete and collision-free exploration of a grid-based environment, with efficient frontier allocation and real-time adaptability. These findings validate the robustness and applicability of the approach, highlighting its potential for deployment in scalable, autonomous, and cooperative exploration scenarios across structured and unstructured environments.

For future work, this research will be extended by adapting the proposed frontier-based exploration algorithm to support cooperative deployment in larger and more complex environments. To enable decentralized coordination within the swarm, a stigmergy-inspired mechanism will be explored, where digital pheromones are employed as an indirect communication medium. By embedding environmental markers as carriers of information, drones will be able to coordinate exploration activities without relying exclusively on direct inter-agent communication. This strategy is anticipated to significantly improve the scalability, robustness, and efficiency of multi-drone exploration, making the approach more suitable for real-world scenarios characterized by dynamic and uncertain conditions.

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