A Swarm-Based Flocking Control Algorithm for Exploration and Coverage of Unknown Environments

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Abstract: - The exploration of unknown environments can be beneficial for a variety of applications, such as inspection of industrial equipment, environmental monitoring, or search and rescue missions. In order to tackle this problem, swarm robotics has emerged as a promising approach due to its ability to leverage the collective behavior of a group of robots to explore an area efficiently. This paper proposes a swarm-based control algorithm for exploration and coverage of unknown environments. The algorithm utilizes short-range distributed communication and sensing among agents, with no central unit, to coordinate the swarm's navigation and search tasks. This sensing is prioritized in the outermost agents of the swarm to reduce processing and energy costs, and these positions can be rotated with other agents in the swarm. The formation rules that keep the system cohesive are simple and independent of the individual robot characteristics, enabling the use of heterogeneous agents. The performance of the proposed strategy is demonstrated through experiments in coverage and search tasks, and compared with other swarm strategies. The results show the effectiveness of the proposed algorithm for exploration and coverage of unknown environments. The research presented in this paper has the potential to contribute to the development of more efficient and effective swarm-based exploration and coverage strategies.

Key-Words: - Coverage, exploration, flocking control, robotics, swarm-based, unknown environments

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1 Introduction

The exploration of unknown environments is an essential aspect of many applications, including environmental monitoring, crop analysis and monitoring, healthcare, industrial equipment inspection, and search and rescue missions, military applications, and space exploration, [1], [2]. Robotics has become an increasingly popular approach to explore unknown environments, with swarm robotics emerging as a promising technique due to its ability to utilize the collective behavior of a group of robots to explore an area efficiently, [3]. Swarm-based control algorithms have been developed to enable the coordination of a swarm's navigation and search tasks in an unfamiliar environment.

Swarm Robotics is a technique that replaces a single robot with a group of agents of simpler and cheaper design with limited processing and sensing capabilities, but with the ability to self-organize into a multi-agent system inspired by behaviors observed in nature, [4]. One such behavior is the Flocking Behavior, derived from migratory birds and modeled from basic behaviors that enable functional replication of these systems, [5], [6]. Numerous experiments have demonstrated the flocking dynamics' ability to solve problems in complex environments, such as aquatic and aerial tasks, [7], [8].

The basic rules of behavior for achieving flocking in a multi-agent system were postulated by Reynolds in 1986, [5]. These rules establish criteria for each agent's motion strategy in the system to avoid collision, perform velocity matching according to its neighbors' motion, and define a flocking axis. The performance of each behavior is measured by metrics on the group's area and polarization, [9], [10]. While the flocking strategy prioritizes the distance between agents, there is another strategy, line flocking, in which agents move in a V-shape, similar to geese migrating. However, the basic rules of cluster flocking can also give rise to line flocking, [11].

In light of the aforementioned challenges, the primary aim of this research is to propose, implement, and evaluate a novel swarm-based control algorithm for the exploration and coverage of unknown environments. More specifically, we seek to address the issues of efficient task coordination, robustness and resilience, resource utilization, and adaptability of the swarm system. We achieve this through the use of distributed communication and sensing strategies, coupled with rotation of roles within the swarm to optimize processing and energy use. Furthermore, the proposed algorithm is designed to function effectively with heterogeneous agents, thereby enhancing its practical applicability in real-world scenarios. It is our intention to demonstrate, through rigorous experimental trials, that our proposed approach not only improves upon the limitations of current swarm strategies, but also contributes substantively to the ongoing evolution of swarm robotics.

Despite the growing interest in autonomous robots for exploring unknown environments, current approaches have limitations that can hinder their effectiveness. For example, single-robot approaches may have poor scalability, limited coverage area, and struggle to adapt to complex environments, while swarm-based approaches face challenges such as robustness and resilience, uncertainty, and efficient coordination of navigation and search tasks, [12]. To address these limitations, this paper proposes a swarm-based control algorithm that utilizes short-range distributed communication and sensing among agents to coordinate the swarm's tasks in an unfamiliar environment, [13]. By prioritizing sensing in the outermost agents of the swarm, the proposed algorithm reduces processing and energy costs, [14]. Moreover, the simple formation rules that keep the system cohesive are independent of individual robot characteristics, allowing for the use of heterogeneous agents. This paper contributes to the development of more efficient and effective swarm-based exploration and coverage strategies.

Exploring unknown environments using swarm-based robotics poses several technical challenges that need to be addressed for effective performance, [15], [16]. Firstly, swarm-based systems must ensure the robustness and resilience of the multi-agent system to maintain the collective behavior despite individual agent failure or communication loss, [17]. Secondly, swarm-based systems require efficient coordination of navigation and search tasks, which can be complicated by the uncertainty and dynamic nature of the environment, [18]. Thirdly, efficient use of available resources, such as processing power and energy, is critical for swarm-based systems, especially for long-term operations, [3]. Finally, the design and implementation of swarm-based systems must be flexible enough to adapt to different environments, tasks, and agent characteristics, as well as to integrate with existing systems.

The paper is organized as follows. Section 2 describes the context and relevant previous research. Section 3 presents preliminary concepts, including the interaction between the robots, the flocking rules, and and the communication strategy between agents. Section 4 presents the strategy of our algorithm, as well as the implementation considerations. Section 5 summarizes the results achieved in the laboratory tests. Section 6 presents further extensions and concludes the paper.

2 Background

Autonomous robots can be utilized for various applications, including environmental monitoring, crop analysis and monitoring, industrial equipment inspection, and search and rescue missions. These applications typically require robots to operate in unknown environments, and thus require effective obstacle avoidance and exploration strategies. Reinforcement learning (RL) based control has been studied as a potential solution for obstacle avoidance in autonomous underwater vehicles (AUVs), [19]. However, standard one-step Q-learning based control has a tendency to explore all possible actions at a given state, which may lead to an increased number of collisions. Modified Q-learning based control approaches have been proposed to deal with this problem in unknown environments, [20].

Target search control of AUVs in underwater environments has also been studied using deep RL and a grid map of the search environment, [21]. In order to enhance the area coverage of unmanned aerial vehicle (UAV) swarms, a novel mobility model that combines an Ant Colony algorithm with chaotic dynamics has been presented, [22]. This model has been extended by the addition of a collision avoidance mechanism and testing its efficiency in terms of area coverage by UAV swarm.

Cooperative exploration strategies have been proposed for multiple mobile robots, which reduce the overall task completion time and energy costs compared to conventional methods, [3]. Hex-decomposition-based coverage planning algorithms have also been proposed for unknown, obstacle-cluttered environments, [23]. In addition, a novel swarm-based control algorithm for exploration and coverage of unknown environments, while maintaining a formation that permits short-range communication, has been proposed, [24].

Furthermore, agents cannot visit arbitrary locations in many applications due to *a priori* unknown safety constraints, which has led to the development of efficient density learning algorithms for solving the coverage problem while preserving the agents' safety, [25]. The development of effective obstacle avoidance and exploration strategies is crucial for the success of autonomous robots in a variety of applications.

3 Problem Formulation

In recent years, multi-agent systems have become increasingly popular due to their ability to perform tasks more efficiently than a single agent system. A multi-agent system consists of n agents, which can be robots in their physical implementation, operating in a closed environment $\mathcal{W} \subset R^2$ that is bounded by $\partial\mathcal{W}$.

The environment includes finite obstacles that form a set $\mathcal{O}$ of areas that are inaccessible to the robots, and a free navigation space E defined by $\mathcal{W} - \mathcal{O}$. The behavior of the system is a result of the interaction of each agent, which operates autonomously without a central control unit. The behavior is determined by a set of basic rules that guide the agent to move towards the destination point while avoiding collisions with obstacles and other agents and maintaining formation. These rules are specified by the agent's velocity $\dot{\boldsymbol{x}}i\,(t)$ and orientation $\theta i\,(t)$, which are tuned based on the system's behavioral policy and sensed information in the environment. However, not all agents perform environmental sensing, only those in the outer layers of the system, while others maintain communication and sensing with other agents.

In more mathematical detail, each agent is represented as a_i for $i \in 1, 2, ..., n$ where n is the total number of agents in the system. Each agent is associated with a state vector s_i consisting of its position $\boldsymbol{x}i\,(t)$ and orientation $\theta i\,(t)$. The velocity vector $\dot{\boldsymbol{x}}_i\,(t)$ is derived from the state vector and is used to determine the agent's movement in the next time step based on the system's behavioral policy and the agent's local sensing information.

Task allocation within the system is another critical aspect that we aim to address in this research. Since the agents in the system can be heterogeneous, the task allocation should account for the varying capabilities and available resources of each agent. We propose a dynamic task allocation approach in which the roles of agents, such as sensing the environment and communicating with other agents, are rotated based on their current state and the overall task requirements. The effectiveness of this task allocation strategy is quantified through measures like system efficiency, task completion time, and the utilization of agent resources.

The performance of our multi-agent system is evaluated based on several measures. These include the overall coverage of the environment, the time taken to complete the task, and the robustness of the system in terms of its ability to adapt to agent failures or loss of communication. We also examine the resource usage of the system in terms of the computational and energy demands placed on the agents. Through our proposed control algorithm, we aim to improve these performance measures, demonstrating the efficacy of our approach in the context of exploration and coverage of unknown environments.

One of the advantages of a multi-agent system is that it allows for the formation of a swarm of robots that can be heterogeneous. This means that each agent can have different capabilities and sensors, allowing for a more efficient distribution of tasks. Additionally, the distributed architecture of the system enables each agent to exchange information with neighboring agents directly without relying on a central processing unit. This architecture is robust as the loss of a subset of agents does not significantly impact the overall performance of the system in completing the task. However, implementing such a system on low-cost hardware with limited sensing and communication capabilities presents a significant challenge. Nonetheless, the potential benefits of multi-agent systems make them an attractive research area in robotics.

4 Methods

The research problem concerns the coverage of an observable but unknown environment, with restrictions on processing and communication capabilities of swarm robots. To conduct our experiments, we built a system consisting of simple differential robots assembled with 3 mm acrylic plates, equipped with servo motors that provide a maximum linear displacement speed of 37.4 cm/s, and an Espressif Systems ESP32 microcontroller (Fig. 1). We use an RPLIDAR A1M8-R6 as a distance sensor. The environment's limits and obstacles $\mathcal{O}$ are pre-established, but their position within those limits is unknown. To address this problem, we propose a distributed (decentralized) solution using Bluetooth Low Energy (BLE) v4.2, which has a maximum transmission speed of 1 Mbps and an approximate range of 50 m. The use of BLE technology allows for short-range communication and reduced power consumption, making it a suitable option for low-cost and low-power robots. The ESP32 microcontroller has built-in BLE support, making it an ideal platform for implementing our solution. The use of decentralized communication and control reduces the need for a centralized control unit, providing a robust and fault-tolerant system that can continue operating even if some robots fail. This approach enables each robot to make decisions based on local readings and interactions with neighboring robots, facilitating the coverage of the unknown environment with limited resources.

To ensure high precision and efficiency in the coverage task, our scheme utilizes a two-dimensional local coverage matrix that is stored in the memory of each robot's ESP32 microcontroller. This matrix is composed of cells, whose size defines the resolution with which the environment is divided into regions, and which is related to the actual size of the robots (robot's shadow in the environment). Each row of the matrix corresponds to a section of the region, and each column corresponds to a robot. The size of the matrix is defined in advance in the robot's code and considers both the number of robots in the environment and the expected distance between agents of the system. If the robot is in an undiscovered or covered cell, it

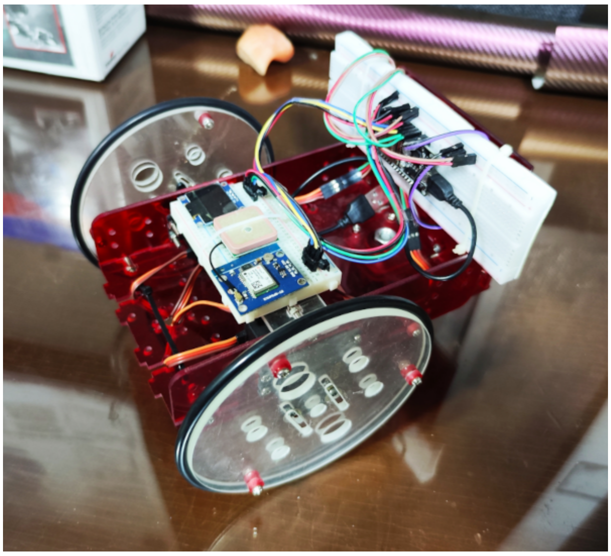

Figure 1: Differential robot used in laboratory tests

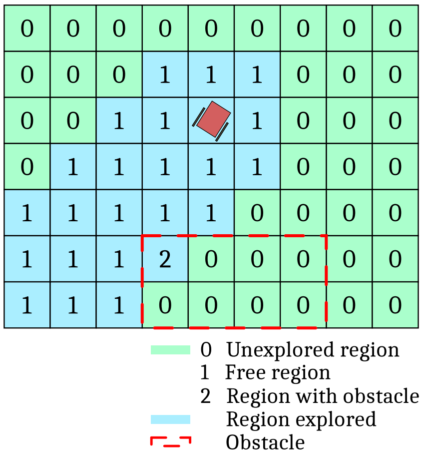

Figure 2: An example of a local coverage-obstacle CO matrix of the agent

is marked with a 1; if the robot detects an obstacle in the cell, the cell is marked with a 2; otherwise, it is marked with a 0. This local coverage-obstacle matrix of the agent is called the CO matrix (Fig. 2).

To reduce network load and minimize the impact of issues such as loss of line-of-sight between pairs of robots, when the distance between two agents is smaller than the communication radius, they exchange their local CO matrices. This localized sharing of CO matrices is facilitated by swarming movements since the robots are continually pulled together due to the cohesion force that controls their movement. The advantage of using a local CO matrix is that it enables each robot to have a detailed map of the environment that can be used to plan its movements and avoid obstacles, without the need for a centralized processing unit. Moreover, the use of short-range communication facilitated by the swarm movement reduces the impact of communication delays and failures, increasing the overall efficiency of the coverage task.

The robots attempt to navigate to the nearest unexplored region according to the gradient of the search sensor. The search sensor is the sensor installed on the robot capable of detecting the particular signal emitted by the navigation target point (such as a gas signal in the case of gas leak detection). This signal can propagate in different ways in the environment according to the nature of the signal itself. For practical purposes, in this study, it is assumed that the signal power decreases linearly as it propagates, so its intensity at the target point is maximum, and minimum in the concentric circle around the target point with radius equal to the propagation distance. This behavior forms the search gradient in the environment. The value of the gradient detected by the robot, together with the unexplored regions, sets the navigation route for the robots at the edges of the swarm. This route is established only by the robots at the front of the system, identified by the direction of the system's advance. The robots in the other peripheries behave like internal robots until the system changes its direction of advance. The rest of the system navigates maintaining the organized structure of the system. The distances between robots are programmed in advance in the microcontroller and controlled through the LiDAR and CO matrices of each agent. Over time, and depending on the battery capacity in the robots, the robots at the periphery of the swarm exchange positions with the robots inside the system.

To minimize collisions between agents, a repulsion parameter is incorporated based on the distances detected by the LiDAR, which takes into account the distance between agents, their speed, and the CO matrix of the robot. This parameter is crucial in environments where there are obstacles or when robots are navigating in close proximity to one another. It helps to maintain the desired separation distance between agents, which is necessary to prevent collisions while ensuring efficient exploration and coverage. The repulsion parameter is dynamically adjusted based on the current sensor readings, and it is integrated into the agents' decision-making process to ensure safe and effective navigation. Additionally, the repulsion parameter can be adjusted to meet specific environmental conditions, such as in highly cluttered environments, where a higher repulsion parameter may be needed to avoid collisions.

The proposed swarm-based control algorithm was designed using a variety of elements, including sensors, communication modules, and actuators. The selection criteria for each of these elements were based on their availability, robustness, accuracy, energy consumption, and cost. The advantages of each of these elements were considered when selecting the best components for the prototype. The performance of the proposed algorithm was evaluated using experiments in coverage and search tasks. The most important characteristics and parameters used to characterize the system performance included energy consumption, accuracy, and efficiency.

The complete algorithm is summarized below:

1. Initialize the robots with the following:
    - Differential drive system using servo motors
    - RPLIDAR A1M8-R6 distance sensor
    - ESP32 microcontroller with built-in BLE support
    - 2D local coverage matrix (*CO* matrix) with cells of defined size
2. Define the environment limits and obstacles $\mathcal{O}$, and mark them on the *CO* matrix.
3. Implement decentralized communication and control using BLE technology.
4. Initialize the *CO* matrix with values of 0 for undiscovered or covered cells.
5. Begin exploration of the environment with swarm of robots by following the steps:
    - Calculate the gradient of the search sensor and locate the nearest unexplored region.
    - Calculate the navigation route for the robots at the edges of the swarm based on the gradient and unexplored regions.
    - The robots at the front of the swarm navigate according to the established route.
    - The robots in the other peripheries of the swarm navigate maintaining the organized structure of the system.
    - The distances between robots are controlled through the LiDAR and *CO* matrices of each agent.
    - Over time and depending on battery capacity, robots at the periphery of the swarm exchange positions with the robots inside the system.
6. Implement a repulsion parameter to minimize collisions between agents.
    - The repulsion parameter takes into account the distance between agents, their speed, and the *CO* matrix of the robot.
    - The repulsion parameter is dynamically adjusted based on the current sensor readings to ensure safe and effective navigation.
    - In highly cluttered environments, the repulsion parameter is adjusted to avoid collisions.
7. When the environment is fully covered, end the exploration process.

5 Findings and results

Four performance metrics are used to evaluate the algorithm: two related to exploration and coverage performance, and two related to self-organizing formation control. The first metric, coverage percentage (*CP*), measures the percentage of the known region covered by any robot of the system. *CP* is defined as the ratio between the number of covered cells and the total number of cells to be covered in the task. The second metric, turnaround time (*TT*), summarizes the coverage performance in terms of the time taken for the robots to indirectly cover the known environment, including mapping all unknown obstacles. The third metric, grouping metric (*G*), estimates how closely a set of robots are clustered together. *G* is defined as the summation of the average distances between agents in all the robots in the system at a given moment, relative to the population size. Finally, the fourth metric, order metric (*C*), computes how similarly the robots are aligned. *C* is defined as the summation of the average relative velocities between agents in all the robots in the system at a given moment, relative to the population size.

We conducted multiple experiments in a 2×3 m rectangular environment, with different obstacle configurations $\mathcal{O}$ and population sizes, while ensuring sufficient free space for robot movement. Search tasks involved different types of destination points, including zero signal emission, one target point with signal, and two or three target points with different magnitudes of emitted signals. For simplicity, we used two types of signals, sound and visible light from LEDs. In the experiments, we recorded both the system's ability to find the target points (task success) and the mean and standard deviation of the four metrics (Table 1).

Although the robots used in the experiments have the same design (Fig. 1), they were constructed by the research group, resulting in operational differences between the prototypes. All robots moved at different maximum speeds despite using the same type of wheels and servo motors, and even the behavior of the

Table 1: Comparative performance of the algorithm against different test conditions. The obstacles remained constant in these results

Test conditions	Real laboratory tests	Simulations
• n = 4 robots • Trials = 10 • Target points with signal emission = 0	CP = 100%±0	CP = 100%±0
	TT = 1128 s ± 56.6	TT = 1020 s ± 32.1
	G = 2.68 m ± 0.21	G = 1.89 m ± 0.13
	C = 0.17 m/s ± 0.01	C = 0.21 m/s ± 0.01
• n = 4 robots • Trials = 10 • Target points with signal emission = 1 (light)	CP = 100%±0	CP = 100%±0
	TT = 820 s ± 7.6	TT = 992 s ± 3.5
	G = 2.10 m ± 0.40	G = 1.51 m ± 0.11
	C = 0.21 m/s ± 0.01	C = 0.28 m/s ± 0.01
• n = 4 robots • Trials = 10 • Target points with signal emission = 2 (light)	CP = 100%±0	CP = 100%±0
	TT = 882 s ± 4.6	TT = 753 s ± 2.1
	G = 1.78 m ± 0.14	G = 1.64 m ± 0.37
	C = 0.12 m/s ± 0.01	C = 0.12 m/s ± 0.01
• n = 4 robots • Trials = 10 • Target points with signal emission = 3 (light)	CP = 100%±0	CP = 100%±0
	TT = 822 s ± 12.4	TT = 697 s ± 9.8
	G = 1.74 m ± 0.52	G = 1.38 m ± 0.22
	C = 0.18 m/s ± 0.02	C = 0.23 m/s ± 0.01

two wheels on the same robot was different. These functional variations served to evaluate the performance of the system with a heterogeneous structure, deliberately forcing the agents' velocities and behavior to be markedly different. In our experimental setup, the robots are controlled by an on-board ESP32 microcontroller. We used 360-degree LiDAR sensors for distance detection.

The robots' movement in the environment was captured by a digital camera, and the frames were processed externally with Python. The location information was transmitted to the robots every 50 ms. These tests were performed indoors; GPS mounted on each robot is envisaged to replace this form of localization in outdoor environments. The CO matrices for each robot were shared with neighboring robots at an update rate of 25 ms. The proposed algorithm was implemented on each robot, ensuring that if one of the robots fails due to hardware problems, the remaining robots can still complete the task. In our experimental simulations, the same settings were implemented using Python. For measurement purposes, we assume that once all cells in the local map of any robot are covered directly or indirectly, a message *completed task* is sent to the remaining robots, and the experiment ends.

The benefits of our study are multifaceted, as we tackle critical issues in swarm robotics, particularly the exploration and coverage of unknown environments. Firstly, our proposed algorithm exhibited strong performance metrics in all the conducted tests. The consistent 100% coverage of the environment demonstrates the algorithm's robustness and reliability, a significant advantage for real-world applications where complete coverage is essential.

Secondly, the algorithm's successful operation amidst the heterogeneity of the swarm - due to operational differences in robots - validates its capability to handle disparities in individual agents. This is a significant stride towards more practical and cost-effective swarm systems where agent uniformity can't be guaranteed.

Thirdly, our proposed dynamic task allocation strategy and self-organizing formation control exhibit great promise in enhancing the efficiency of swarm systems. It effectively minimizes resource usage and optimizes task completion time while maintaining the robustness of the system in case of individual robot failure.

Finally, the utilization of a distributed control approach enables scalability and robustness, allowing the swarm to handle a larger and more complex environment without a significant performance drop or the need for an overarching centralized control unit. This research, therefore, paves the way for advancements in real-world applications like environmental monitoring, search and rescue missions, and space exploration.

Despite variations in total task times for similar conditions, all developed tests achieved a 100% coverage of the environment (CP = 100% in all cases). The differences in times are not significant at the 95% confidence level.

6 Discussion

The research presented in this paper proposes a distributed, decentralized solution for the coverage of an unknown environment using a swarm of simple differential robots with limited processing and communication capabilities. The proposed approach utilizes Bluetooth Low Energy (BLE) communication technology to achieve short-range communication between robots, reducing power consumption and enabling decentralized communication and control. The use of a local CO matrix enables each robot to have a detailed map of the environment that can be used to plan its movements and avoid obstacles, without the need for a centralized processing unit. The proposed algorithm incorporates a repulsion parameter to minimize collisions between agents and enable safe and effective navigation.

The experimental results show that the proposed algorithm achieved a 100% coverage of the environment in all cases. The proposed algorithm was evaluated using four performance metrics: coverage percentage (CP), turnaround time (TT), grouping metric (G), and order metric (C). The evaluation demonstrated that the proposed algorithm achieved high precision and efficiency in the coverage task.

The proposed algorithm has several advantages over centralized approaches. First, decentralized communication and control reduce the need for a centralized control unit, providing a robust and fault-tolerant system that can continue operating even if some robots fail. Second, the use of short-range communication facilitated by the swarm movement reduces the impact of communication delays and failures, increasing the overall efficiency of the coverage task. Third, the use of a local *CO* matrix enables each robot to have a detailed map of the environment, which can be used to plan its movements and avoid obstacles, without the need for a centralized processing unit. Fourth, the incorporation of a repulsion parameter minimizes collisions between agents and enables safe and effective navigation.

The algorithm provides a distributed, decentralized solution for the coverage of an unknown environment with limited resources. The use of short-range communication, local *CO* matrices, and a repulsion parameter enables efficient and precise coverage while reducing the impact of communication delays and failures and minimizing collisions between agents. The experimental results demonstrate the effectiveness and efficiency of the proposed algorithm, making it a promising approach for various applications in different fields. Future work includes testing the proposed algorithm in outdoor environments and integrating it with GPS localization for improved accuracy and performance.

7 Conclusion

The main findings and contributions of this paper include the proposal of a novel swarm-based control algorithm that enables the coordination of a swarm's navigation and search tasks in an unfamiliar environment. The proposed algorithm utilizes short-range distributed communication and sensing among agents, with no central unit, and prioritizes sensing in the outermost agents of the swarm to reduce processing and energy costs. The algorithm also maintains simple formation rules that are independent of individual robot characteristics, allowing for the use of heterogeneous agents. This research has the potential to contribute to the development of more efficient and effective swarm-based exploration and coverage strategies. Possible future work includes the implementation of the proposed algorithm in larger environments and with more complex tasks.

Despite the promising results, our research is not without its limitations. Our experiments were conducted in a relatively controlled indoor environment. While this was sufficient for validating the proposed algorithm, real-world scenarios can be considerably more challenging and unpredictable. External factors like weather conditions, signal interferences, and unstructured terrain can significantly impact the performance of the swarm, suggesting a need for further robustness in our algorithm to tackle such uncertainties. Another limitation is that our algorithm, in its current state, may not perform as effectively when scaled up for larger environments or more complex tasks. It's important to note that as the number of robots and the complexity of tasks increase, the need for efficient and robust communication among robots also increases. The impact of communication delays, packet loss, and other network issues will need to be addressed in future iterations of the algorithm.

In light of these limitations, a few improvements are suggested. Firstly, introducing adaptive behavior in the algorithm, allowing the swarm to adjust their formation and exploration strategy based on the immediate environment, could enhance the performance of the swarm in complex and dynamic environments. Secondly, it could be beneficial to incorporate machine learning techniques to enable the swarm to learn from past experiences and continuously improve their performance over time.

As for future work, we aim to test the proposed algorithm in larger and more complex environments, including outdoor settings with real-world challenges. We also plan to extend our research to explore how the swarm can adaptively respond to dynamic changes in the environment and optimize their strategy in real-time. Furthermore, integration of our algorithm with more advanced communication technology to improve network resilience and robustness is another avenue we are keen to explore.

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