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Original Article

Coverage-Enhanced Unknown Area Exploration and Mapping Technique for a Multi-Robot System

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Abstract *- An active task distribution algorithm is presented to realize the multi-robot exploration and mapping in new environments. During such missions, when covering unexplored areas, coverage has to be done in an efficient manner to provide a good performance. Inefficient task assignment usually results in the re-use of explored regions by robots. This leads to the wastage of fuel, time, and communication resources. The strategy employed by the proposed approach maximizes area coverage by providing dynamic task assignments so that each robot can target queues or recently covered and unexplored areas. It saves time, increases the productivity of the individual robots, and accelerates the entire mapping process by reducing duplication. The configuration was experimented with using the Robot Operating System (ROS) and the Gazebo simulation platform. These tests were done indoors, where there were obstacles that made the environment realistic. The findings indicated significant increases in the exploration speed, coverage factor, and mapping completion rate as compared to those of the existing methods. After a visual examination of the simulation results, it was clear that very few duplicate paths were obtained. This cements the fact that the allocation technique assists robots in a more efficient operation and with improved resource management. This is achieved through enhanced coverage of areas and reduction of unintended motions, making the multi-robot performance in complicated and unfamiliar terrains. It offers a scalable solution to such applications as search and rescue, environmental monitoring, and autonomous inspection.*

Keywords *- Multi-Robot Systems, Dynamic Task Allocation, Exploration of Unknown Territory, Mapping of Unknown Territory, Territory Coverage.*

1. Introduction

In the last ten years, multi-robot systems have caught many eyes as they provide fast and efficient workplace coverage in both known and unknown environments, and also perform multiple tasks [1, 4, 19, 26]. They are used in planetary exploration, environmental monitoring, industrial inspection, and search-and-rescue applications, where the high-speed coordinated actions of swarms of robots have shown benefits over those of individual robots in coverage rates, robustness, and success rates [5, 6, 20, 24, 27]. The fundamental problem is task distribution -allocating each robot to venture into different and one of higher priority while curbing duplication in travelling, resource use, as well as mapping [7, 10, 15].

To address these challenges, this paper proposes a coverage-enhanced dynamic task allocation algorithm that integrates Information Gain Factor (IGF), Travel Cost (TC), and Proximity Penalty (PP) within a Z-score normalization framework to ensure balanced, adaptive, and efficient frontier assignment. By combining frontier detection, clustering-based prioritization, and dynamic reallocation, the method reduces redundancy, optimizes coverage, and adapts to changing environmental conditions in real time.

The remainder of this paper is organized as follows: Section 2 discusses some research works related to multi-robot systems. Section 3 formulates the problem and its challenges. Section 4 details the proposed methodology, including the allocation algorithm and coverage maximization strategy. Section 5 describes the experimental setup and scenarios. Section 6 presents results and comparative analysis. Section 7 discusses the broader implications and scalability of the approach, and Section 8 concludes with future research directions.

2. Literature Review

Initial solutions were based on the use of static or semi-static allocation protocols [17, 25]. Although those perform well in structured environments, they fail in less structured environments when the priorities of the exploration actions change quickly [1, 4, 19]. Case in point, Zhao and Hwang [1] provided an exploitation-seeking deep deterministic policy gradient to active SLAM in an indoor space, and Lau et al. [2]

presented a multi-AGV exploration temporal memory to increase the level of flexibility. Yin et al. [3, 17] proposed a better way or improved path planning through a hybrid clustering-based RRT method, but its properties of adaptation in a highly dynamic environment were still low. By comparison, Feng et al. [4] promoted real-time, data-based tasking, and Mukhopadhyay et al. [5, 29] made developments in multi-robot exploration with multiple Rapid Exploring Randomized Tree (RRTs) to enhance mapping in unstructured domains. Exploration-RRT [6] was a multi-objective path planning and exploration framework proposed by Lindqvist et al, and RRT* was enhanced by heuristically sampling by Ding et al [7] to cover more efficiently.

Further innovations have targeted exploration efficiency through seeded region-growing techniques [8], hierarchical space exploration [11], and frontier detection methods that improve mapping completeness [9, 10, 14, 15, 19, 20]. For instance, Sun et al. [10] developed frontier detection with reachability analysis to support 2D Graph-SLAM, whereas Yang et al. [11] proposed autonomous exploration for mobile robots in three-dimensional, multi-layer spaces. Clustering-based map segmentation, such as the K-means approach by Goodwin and Nokleby [12, 25], has also been applied to optimize task allocation. Tian et al. [8] used seeded region growing for autonomous exploration, while Tran et al. [16] investigated frontier-led swarming to achieve robust multi-robot coverage in unknown environments.

Cooperative and adaptive strategies have also been explored, including task allocation via frontier trees [13, 21], fast frontier-region detection with parallel path planning [14], and safe, reachable frontier detection algorithms [15]. Graph-based planning methods for simultaneous coverage and exploration [20], coordinated exploration with limited connectivity [22], and low-cost cooperative indoor exploration [23] further demonstrate the diversity of approaches in this field. Map merging techniques [24], robust swarming control [16], and hybrid meta-heuristic optimization, as proposed by Romeh and Mirjalili [27], have shown potential for scalable deployments. Additional contributions from Alitappeh and Jeddisaravi [26] on multi-robot exploration task allocation, as well as recent works by Soni et al. [13, 21] and Filho and Nascimento [24], reinforce the importance of integrated planning and allocation strategies.

Foundational contributions in frontier-based exploration include the multiple RRT framework by Umari and Mukhopadhyay [28], extended in subsequent work [29], and studies on hierarchical clustering algorithms for segmentation and allocation [18]. Research has also addressed multi-robot cooperation in terrestrial environments [19], incremental frontier detection for safe exploration [15], and strategies for dynamic reallocation in changing operational contexts [30]. The previous works [30, 31] explored evolutionary optimization and cost-effective exploration strategies for disaster reconnaissance, while [31] reviewed state-of-the-art dynamic task allocation methods, identifying limitations in adaptability, coverage optimization, and spatial redundancy control.

Despite these advances, persistent gaps remain: (1) many algorithms do not integrate spatial distribution constraints effectively, leading to robots converging on nearby frontiers; (2) real-time adaptability to environmental changes is often insufficient; and (3) balancing information gain, travel cost, and proximity penalties in a unified allocation framework remains underexplored.

3. Problem Description

Multi-robot mapping and exploration systems used in unexplored terrain aim to reduce repetitive exploration activities while maximizing coverage. Mathematically, this can be exactly expressed to provide a basis for understanding and solving the problem.

- Considering: A set of robots $A = \{a_1, a_2, \dots, a_n\}$
- An unknown environment represented as a grid of continuous space E
- Each robot r_i operates over a discrete time horizon T

Let:

- $S_i(t)$ Be the area covered by the robot. r_iAt the time t.
- $S(t) = \cup_{i=1}^{n} S_i(t)$ Be the total area covered by all robots at time t.
- $A_i(t)$ Be the redundant area covered by the robot. a_iAt a time t.

The coverage C and redundancy R can be expressed as:

$$S = \int_0^T |S(t)| dt \tag{1}$$

$$A = \int_0^T \cup_{(i \neq j)} \left|S_i(t) \cap S_j(t)\right| dt \tag{2}$$

Define the task allocation function τsuch that:

$$\tau : A \, x \, T \rightarrow E$$

For each robot $a_i$at a time$t$, the task allocation function $\tau(a_i, t\}$ specifies the area E that the robot should explore.

The objective is to find the optimal task allocation τthat maximizes S and minimizes$A$, while also optimizing the exploration time T.

The optimization problem can be formulated as:
$max_\tau \int_0^T |\cup_{i=1}^{n} S_i(t)| dt$ Subject to

$min_\tau \int_0^T \left|\cup_{i\neq 1}^{n} \llbracket(S\rrbracket_i(t) \cap S_j(t))\right| dt$ Additionally, to incorporate the exploration time T

$min_{\tau} T$ to

$$S(T) = E \tag{3}$$

This guarantees that the multi-robot system, within an ideal time frame, maximizes total coverage while minimizing redundancy in coverage, therefore enabling effective exploration and mapping of the unknown environment.

4. Proposed Dynamic Task Allocation Strategy

The proposed methodology follows a sequential process beginning with environmental perception Figure 1, where each robot acquires sensor data and incrementally updates its occupancy grid representation [1, 9, 10]. Based on the updated map, frontier detection is performed to locate unexplored boundaries that separate known and unknown regions [12, 15, 19]. These frontiers are then spatially grouped using a clustering mechanism to reduce the number of candidate targets while preserving coverage potential [8, 25].

Every found frontier cluster then gets evaluated based on three major metrics including: the Information Gain Factor (IGF), which approximates knowledge gained upon exploration [4, 14]; the Travel Cost (TC), which is the shortest, navigable distance between the current position of a given robot and a frontier [6, 7]; and the Proximity Penalty (PP) which forces certain frontiers to discourage redundant allocations by imposing a kind of penalty defined on those situated in close spatial proximity to other frontiers that were assigned to other robots [16, 22]. In order to compare them, a Z-score standardization process is conducted across these heterogeneous measurements [27], i.e., standardized values are generated, which can be incorporated in a consistent decision model.

Normalization of each metric is performed, and a weighted sum of all the metrics and the weight is chosen based on specific mission priorities and the operational limitations it is subjected to [26]. The allocation module allocates frontiers to robots depending on the utility scores that rank highest and utilizes a priority-based arbitration mechanism in case the robots narrow down to the same target [5, 28]. An event in the environment, when the new frontiers are explored, dynamic obstacles are encountered, or path blockages are identified, prompts the real-time update of the allocation and results in both adaptation and sustained coverage effectiveness [3, 11, 29]. This repeating loop goes on until there is nothing more to discover for available frontiers, thus accomplishing the mission goals...

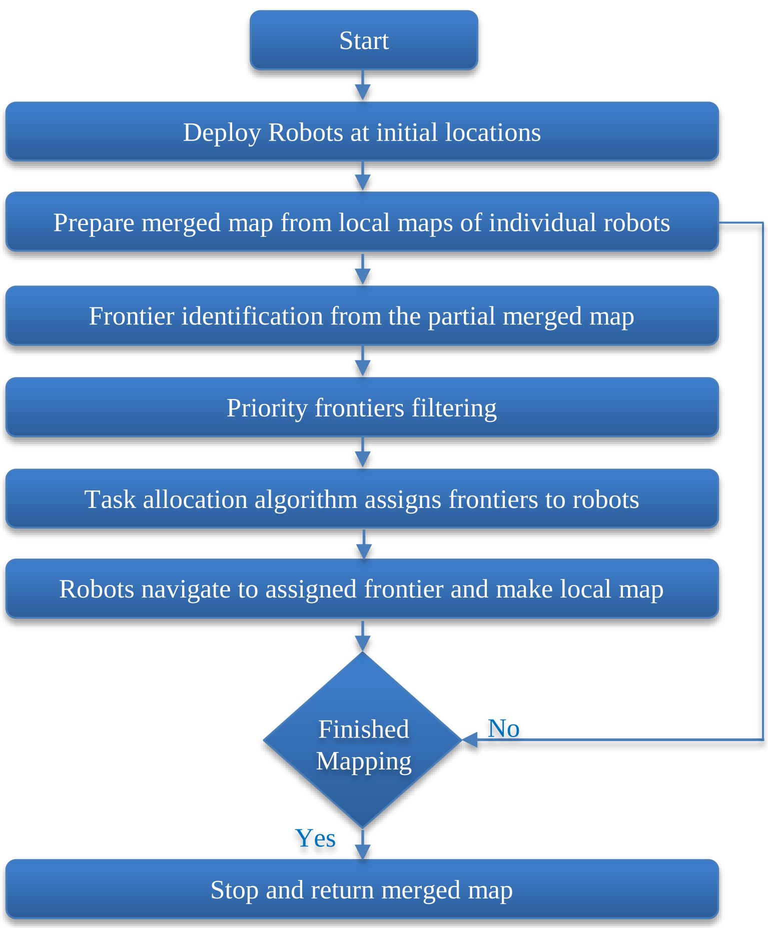

Fig. 1 Flowchart of the developed dynamic task allocation strategy

4.1. Initial Robot Deployment and Calibration

At the start of the allocation process, the relative location and orientations of the robots are highly tuned as they are deployed to pre-selected starting places. The first spatial map is used in the first assignment turn of the frontiers, such that the assignment of the tasks ensures consideration of inter-robot distances to prevent premature redundancy of coverage as well as overlap. The positional calibration is also conducive to the vivid combination of maps, ease in motion planning, and predicted collision avoidance during the mission. Using these initial conditions, the system suffers no exploratory inefficiency as all robots initially launch exploration in a coordinated fashion and therefore has the potential to offer maximum coverage overall.

4.2. RRT-Based Frontier Identification from Partial Maps

The coordinated deployment occurs at calibrated first positions, following which it moves to the exploration process that progresses into the stage of frontier detection within the dynamical task-allocation framework of multi-robot explorations. The point of this work is that it develops the strategies of RRT-based frontier detection suggested by Umari and Mukhopadhyay [28, 29], which allow finding the exploration targets at different distances, efficiently. The algorithm commences with examining the given partially occupied grid map in order to establish the boundaries of explored and unexplored parts. When a frontier has been located, a local RRT-based detector asks the tree established at the current point of the robot to regenerate itself to explore the local area exhaustively. Parallel to this, the world RRT-based detector is building its search tree without reset, scanning the full map step-by-step, and enabling it to detect remote boundaries. The incorporation of local and global detection modes also makes the system have an equal coverage of the near and far regions, hence quicker in the establishment of the unexplored areas and less redundant. Identification of the frontier works is as follows:

1. Acquire the most recent partial map generated by each robot.
2. Define frontiers as the interface between explored and unexplored cells.
3. Apply RRT-based frontier detection:
   – Initialize the RRT using the current known map.
   – Expand tree nodes toward unexplored regions.
   – Mark the boundary cells encountered as valid frontier points.

Table 1. Operational differences between local and global RRT frontier detection

Step	Local RRT frontier detection	Global RRT frontier detection
Initialization	Set the initial vertex and edge set. $V = \{x_{init}\} E = \phi$	
Iteration	Sample a random point in free space. $x_{rand} \epsilon X_{free}$	
	Find the nearest vertex to the random point. $x_{nearest} = argmin_{v \epsilon V} \|\|v - x_{rand}\|\|$	
	Generate a new point using the Steer function. $x_{new} = Steer(x_{nearest}, x_{rand}, \eta)$	
	Check if the new point lies in the unknown region. N $GridCheck(map, x_{nearest}, x_{new}) = \{-1\ if\ unknown, 1\ if\ free\ \} \ 0\ if\ occupied\}$	
	Mark the new point as a frontier and reset the tree if it lies in the unknown region	Mark the new point as a frontier if it lies in an unknown region
	Add the new point to the tree if it lies in freespace. Itf x_{new} is in free space. $V \leftarrow V \cup \{x_{new}\} E \leftarrow E \cup \{(x_{nearest}, x_{new})\}$	

4.3. Priority Frontiers Filtering

Following frontier detection, the system performs a Priority Frontier Filtering process to ensure that robots focus on exploration targets with the highest potential for information gain while avoiding redundant or low-value regions. This stage continuously updates the set of candidate frontiers based on the most recent occupancy grid information, enabling dynamic adaptation to changes in the environment.

Initially, each detected frontier point is treated as an individual group. The clustering process then applies agglomerative clustering using Ward's linkage criterion to merge spatially close frontiers, thereby reducing computational overhead and navigation costs while preserving high coverage potential. The Ward's distance between two clustersS_i And $S$is calculated as:

$$d(S_i, S) = \sqrt{\frac{2.|S_i|.|S_j|}{|S_i|+|S_j|}}.\left|\left|\underline{x_i} - \underline{x_j}\right|\right| \quad (4)$$

In every iteration, the two closest clusters are measured using Ward distance, and are combined, and so on, until what you want as clusters is attained. Then, the centroid of every cluster is taken into account. Each point (x,y) of the centroid of the frontiers gets the grid value g(x,y) that is read off the occupancy map:$\mathrm{g(x, y) = mapData.\,data[index]}$ (5)

$$\mathrm{index\ =\ j\ \times\ width\ +\ i} \quad (6)$$

$$i\ =\ \left(\frac{x - X^{x}{}_{start}}{resolution}\right) \quad (7)$$

$$j\ =\ \left(\frac{y - X^{y}{}_{start}}{resolution}\right) \quad (8)$$

A frontier is considered valid for further exploration only if:

$$\mathrm{g(x, y) \leq\ T_{obstacle}} \quad (9)$$

Where, $\mathrm{T_{obstacle}}$is the maximum allowable grid cost for safe navigation.

With the help of such filtering between the frontiers, the system will take care of places that have a high potential for exploration, and not depend on areas that are dangerous or have a low cost. The targeted performance can minimize unnecessary coverage, amplify resource usage, and elevate total mission efficiency in unfamiliar and on-the-fly conditions.

4.4. Assigning Dynamic Tasks to Robots

After obtaining the set of valid frontiers with the help of the priority filtering procedure discussed in Section 3.3, one must now dynamically assign the exploration targets to the explorer robots with the aim of maximizing coverage efficiency and minimizing redundancy at the same time. Such an allocation framework is a real-time system that reevaluates the assignments when new map information is gathered.

The three basic decision factors, such as information gain, travel cost, and proximity penalty, form a part of the unified revenue function that makes the model able to maintain a balance between the quality of exploration and operational efficiency of the system.

4.4.1. Allocation Model Definition

Let $A = \{a_1, a_2, \dots a_n\}$ Be the set of robots. F= $\{f_1, f_2, \dots f_m\}$ And M be the occupancy grid map of the environment. The objective is to determine the optimal mapping between robots and frontiers so that overall coverage efficiency is maximized.

4.4.2. Metric Definitions

Information Gain

The information gain for a frontier point f_j It is computed based on the number of unknown cells within a circular region of radius r around the frontier. The radius in grid cells is given by:

$$r_{region}\ =\ \left(\frac{r}{mapData.info.resolution}\right) \quad (10)$$

The initial index for the region scan is:

$$initindex = index\ -\ r_{region}\ \times (mapData.info.width\ +\ 1) \quad (11)$$

The total information gain is accumulated by scanning all cells within the defined region:

$$IG(f_j) = \sum_k \epsilon region(f_j)\delta\left(M_{(k=unknown)}\right).A_k \quad (12)$$

Where $\delta(\cdot)$ is an indicator function returning 1 for unknown cells and 0 otherwise, and A_k is the area of cell k Frontiers are retained for allocation only if they satisfy both the information gain and obstacle proximity criteria:

$$Frontier_{valid}\ =\ \{IG(x, y) \geq T_{info}\ and\ g(x, y) \leq T_{obstacle}\} \quad (13)$$

Travel Cost

For each robot r_i and frontier f_jThe travel cost represents the Euclidean distance between the robot's current position and the frontier:

$$C_{ij}\ =\ \left|\left|position(r_i) - f_j\right|\right| \quad (14)$$

Proximity Penalty

This term discourages the assignment of multiple robots to closely located frontiers by imposing a penalty based on the proximity off_j To the frontiers already allocated to other robots:

$$P_{ij} = \frac{\sum_{r_k \epsilon R, k\neq i} \epsilon}{\left|\left|f_j - assigned\ point(r_k)\right|\right| + 1} \quad (15)$$

4.4.3. Normalization

To ensure comparability among metrics with different scales, Z-score normalization is applied:

$$X'\ =\ \frac{X - \mu_X}{\sigma_X} \quad (16)$$

Where μ_x is the mean of x and σ_x Is the standard deviation of x. Applying this to information gain, cost, and proximity penalty:

$$IG'_j = z\_score(IG(f_j)) \quad (17)$$

$$C'_{ij} = z\_score(C_{ij} \quad (18)$$

$$P'_{ij} = z\_score(P_{ij} \quad (19)$$

This standardization prevents any single metric from disproportionately influencing the allocation decision.

4.4.4. Revenue Model

The allocation decision is based on a weighted revenue function:

$$R_{ij} = \alpha . IG'_j - \beta . C'_{ij} - \gamma . P'_{ij} \quad (20)$$

Where α, β, and γ are tunable weights reflecting the relative importance of each factor. The optimal robot–frontier pair a^*, f^*Is then selected as:

Select the robot-frontier pair (a^*, f^*) With the highest revenue:

$$(a^*, f^*) = argmax_{i,j} R_{ij} \quad (21)$$

4.4.5. Task Assignment Algorithm

Algorithm 1: Task Assignment Algorithm

Input: Robot set A, frontier set F, map M, $T_{timeout}$,α, β and γ

Output: Assignment of robots to frontiers

1. Initialize: Set robot positions, thresholds, and parameters
2. Subscribe to Map data: Acquire M and detect F
3. Loop until stopping condition:
   - 3.1. Check task timeouts; mark expired tasks as failed
   - 3.2. Remove failed frontiers from F
   - 3.3. Compute $IG(fj), Cij$ and Pij for all i, j
   - 3.4. Normalize metrics using Eqs. (22)–(24)
   - 3.5. Calculate Rij using Eq. (25)
   - 3.6. Select $(a^*, f^*) = argmax_{i,j} R_{ij}$
   - 3.7. Assign a^* tof^* And record assignment time.
   - 3.8. Plan path P using RRT from $x_{current}$ to x_{goal}
   - 3.9. Update $F_{local} = LocalRRT(x_{current})$ and $F_{global} = GlobalRRT(\mathrm{M})$
   - 3.10. Navigate along the path P while updating map $M = UpdateMap(M, sensor\ data)$
   - 3.11. Navigate while updating M and re-planning if obstacles are detected

Upon arrival, explore locally and merge maps.

The system achieves high-efficiency multi-robot exploration in unknown environments by integrating Dynamic Task Allocation, RRT-based path planning, frontier detection, and incremental map merging. The joint consideration of information gain, travel cost, and proximity penalty ensures that high-value frontiers are prioritized, redundant assignments are minimized, and coverage is maximized. The use of Z-score normalization further guarantees balanced decision-making, preventing any single metric from dominating the allocation process.

5. Experimental Setup

In order to test the performance of the coverage-enhanced dynamic task allocation framework proposed in Section 3, several simulation experiments were performed under varied, but controlled and difficult conditions. It was intended to establish how efficiently the algorithm establishes the coordination of various robots to explore different environments with open spaces and obstacles, thus capturing realistic operational constraints.

They were created using the Robot Operating System (ROS) Noetic on an Ubuntu 20.04 LTS operating system. Simulations were performed in Gazebo. The workstation provided the simulation platform, which had an Intel Core i5 10th-generation processor. The test arena was a TurtleBot3 world, slightly customized to include the wide open spaces and tightly clumped static obstacles, to allow a wide range of navigation challenges to the mapping and frontier distribution.

The three robotic agents deployed in the experiments were a TurtleBot3 Waffle Pi robot, selected because it is compatible with the ROS navigation stack, and a frontier exploration work. Their inbuilt sensors and differential drive enabled them to easily navigate the simulated environment, localize, map, and plan their movements.

Gazebo world had an ordered environment of walls and static barriers, which forced robots, through continuous path planning and assignment of frontiers, when they had navigation constraints. See Figure 2 as an exemplary environment where the shipwreck components are the navigation constraints to which the robots are forced to optimize a series of exploration paths according to the dynamic allocation plan.

Diagnosis on three quantitative measures was used to provide a performance evaluation:

Total exploration time- the total amount of time one takes to explore the environment.

Total Traveled distance -length of path traversed by the complete loop of robots.

Explored the area and the percentage of the environment that was effectively mapped during the mission.

These metrics have been chosen to capture the efficiency aspect (time and distance) and the effectiveness aspect (coverage) of multi-robot exploration. The evaluation involved a known set of constraints and a simulation environment in which all the experiments could be run, which allowed it to attribute the differences in the performance to the proposed allocation strategy itself and not some of the environmental factors.

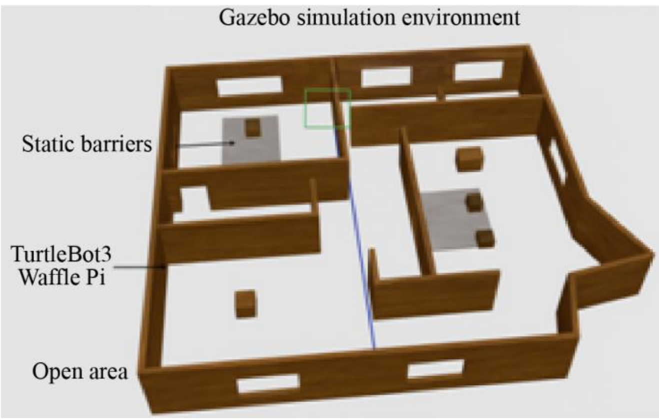

Fig. 2 Gazebo simulation environment used for evaluation of the proposed multi-robot task allocation

Based on the simulation environment reported above, targeted test scenarios were designed to explore the execution behavior of the proposed task allocation algorithm with respect to the various operation conditions. In the main scenario, a fixed obstacle map was set up that contained several walls and other stationary objects, forcing the robots to work around the constraints without suffering excessive, inefficient mapping and exploration. As shown in Figure 2, such a design offered an organized but complex layout that successfully evaluated navigational, frontier allocation, and coordination skills.

In the simulation experiments, there are three performance measures that were considered in order to examine the effectiveness of the suggested solution:

1. Total distance traveled by the entire robot team.
2. Total exploration time required to complete coverage.

By employing a controlled simulation environment with known parameters, nearly all components of the task allocation framework, ranging from frontier detection and filtering to dynamic assignment and coordinated navigation, were rigorously exercised. This ensured that observed results could be directly attributed to the allocation strategy rather than uncontrolled environmental variability.

6. Results and Discussion

The experimental results demonstrate the effectiveness of the proposed coverage-enhanced dynamic task allocation strategy in addressing the multi-robot exploration problem. The evaluation focuses on three performance metrics:

1. Exploration time – total time required for the team of robots to complete the mapping task.
2. Travel distance – total distance traversed by each robot and the robot team collectively.

Experiments were performed in both static and dynamic obstacle environments using the simulation setup described in Section 4. In all scenarios, the proposed approach achieved higher coverage and reduced redundant traversal, thereby improving the spatial distribution of exploration tasks.

6.1. Comparative Analysis with Existing Methods

Following the simulation configuration and performance metrics outlined in Section 4, a direct comparison was performed between the baseline method of Umari et al. [28, 29] (without a coverage penalty parameter) and the proposed method (with a coverage penalty parameter integrated into the allocation framework). Quantitative results are presented in Table 2, reporting per-robot distances, total team distance, and start/finish times for each trial.

From Table 2, it is evident that the integration of the coverage penalty parameter leads to a consistent reduction in both total travel distance and total mapping time. The parameter effectively penalizes allocation of spatially proximate frontiers to multiple robots, minimizing trajectory overlap and enhancing overall coverage efficiency.

Across all five trials, the proposed method achieved an average reduction of 32.4% in total exploration time and a 27.8% reduction in total travel distance compared to the baseline approach. These improvements were consistent across all trials, with no case in which the baseline outperformed the proposed method. This translates directly into lower energy consumption, reduced mechanical wear, and improved operational sustainability for extended missions.

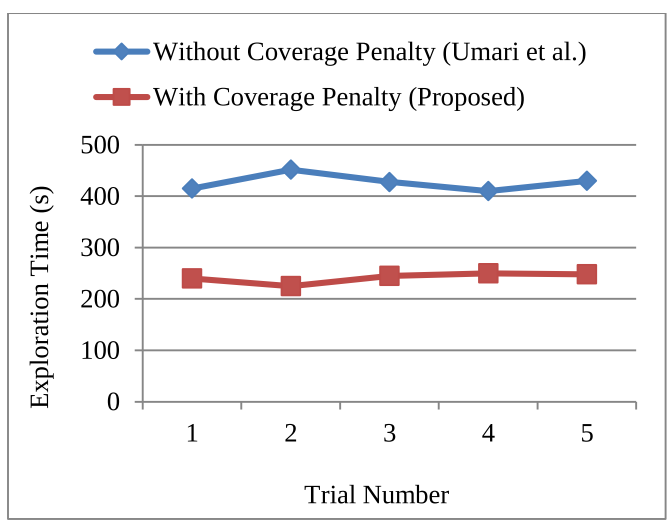

Fig. 3 Comparison of task completion between the algorithm with and without the coverage penalty parameter

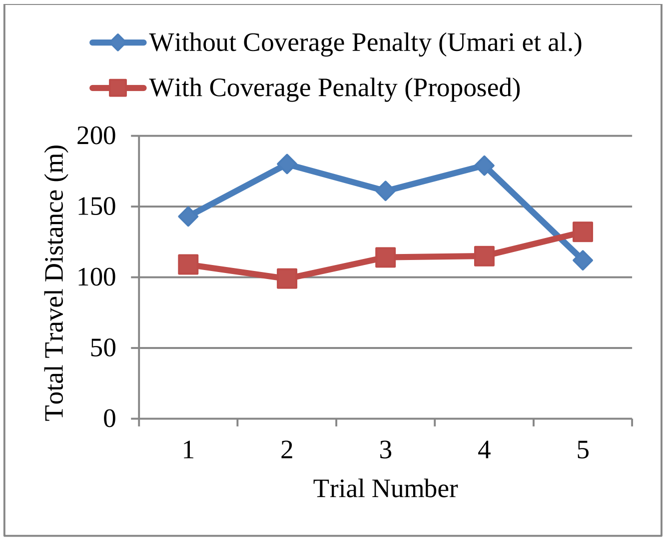

Fig. 4 Comparison of the travel distance of all the robots between the algorithm with and without the coverage penalty parameter

Figures 3 and 4 complement the numerical results by visualizing the performance differences. Figure 3 compares the mapping completion time across five trials, showing that the proposed method consistently outperforms the baseline in terms of speed. Figure 4 compares the total distance traveled by the robot team, where the proposed method yields shorter cumulative travel distances in every trial.

6.1.1. Qualitative Analysis of Trajectories

To further illustrate these differences, Figures 5-7 present the exploration trajectories generated by the baseline algorithm [28, 29] in three representative trials. Each color represents a different robot-blue (TurtleBot tb_0), red (TurtleBot tb_1), and green (TurtleBot tb_2). These trials reveal substantial trajectory overlap, with multiple robots visiting the same regions multiple times. This redundancy increases travel distance and can leave some unexplored, lowering mapping efficiency.

Figures 8-10 depict the exploration trajectories for the proposed method with the coverage penalty parameter. Here, trajectory overlap is noticeably reduced, and the robots' coverage is more uniformly distributed. The spatial separation of exploration paths minimizes wasted motion and ensures that all regions of the environment are efficiently mapped.

The combination of quantitative metrics, statistical improvements, and qualitative trajectory analysis confirms that the proposed coverage penalty parameter significantly enhances multi-robot exploration performance. By balancing information gain, travel cost, and proximity penalties in the allocation process, the method ensures optimal distribution of exploration tasks, reduced redundancy, and improved overall mapping efficiency.

Table 2. Results and comparison of the proposed task allocation strategy and the existing RRT algorithm (Umar et al.)

	Trial No	Start time(s)	Finish time(s)	Distance travelled in meters.			
				turtlebot1	**turtlebot 2**	**turtlebot 0**	**Team of robots**
Without coverage penalty parameter (Umari et al.)	1	38	453	42.98	43.53	56.65	143.16
	2	29	480	59.85	59.85	59.85	179.56
	3	24	450	58.27	51.29	51.29	160.84
	4	36	446	63.88	61.96	53.29	179.13
	5	28	460	30.84	16.83	64.66	112.33
	Trial No	**Start time(s)**	**Finish time(s)**	**Distance travelled in meters.**			
				turtlebot1	**turtlebot 2**	**turtlebot 0**	**Team of robots**
With coverage penalty parameter (Proposed concept)	1	31	270	37.85	39.55	31.90	109.29
	2	30	258	33.49	40.30	25.33	99.12
	3	28	273	34.60	38.73	40.50	113.83
	4	22	272	44.42	31.05	39.20	114.67
	5	28	276	42.08	39.50	51.24	132.82

In all three trials, the exploration trajectories exhibit substantial overlap among the robots, resulting in an increased cumulative travel distance for the team. Several regions are revisited multiple times by all three robots, while certain areas remain unexplored. Such redundant traversal not only leads to inefficient use of operational time and energy but also limits overall coverage, highlighting a key limitation of the baseline algorithm.

The following images (Figures 7, 8, 9) are the path travelled by the team of robots using the algorithm with the coverage penalty parameter.

It shows the path taken by these robots in the first three trials. The three colours, red, blue, and green, are the paths of the three robots.

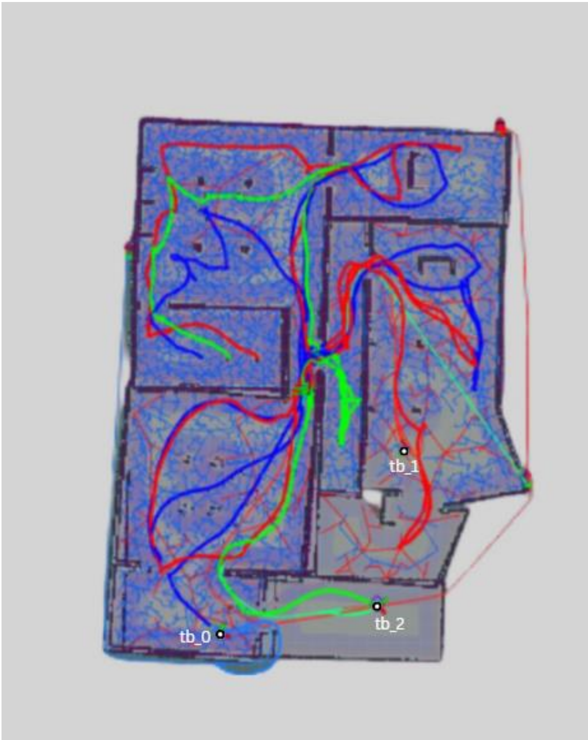

Fig. 5 Trial 1 output of the task allocation algorithm without the coverage penalty parameter (Umari et al. [28, 29]). Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

Fig. 7 Trial 3 output of the task allocation algorithm without the coverage penalty parameter (Umari et al. [28, 29]). Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

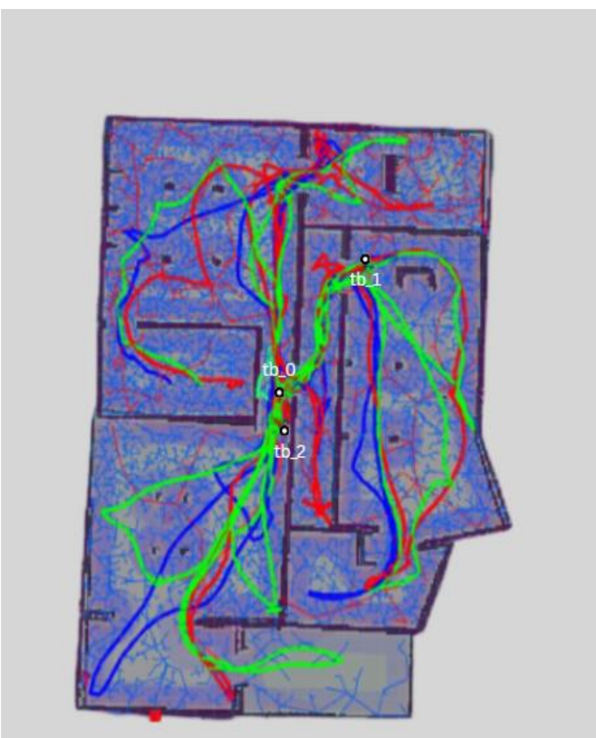

Fig. 6 Trial 2 output of the task allocation algorithm without the coverage penalty parameter (Umari et al. [28, 29]). Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

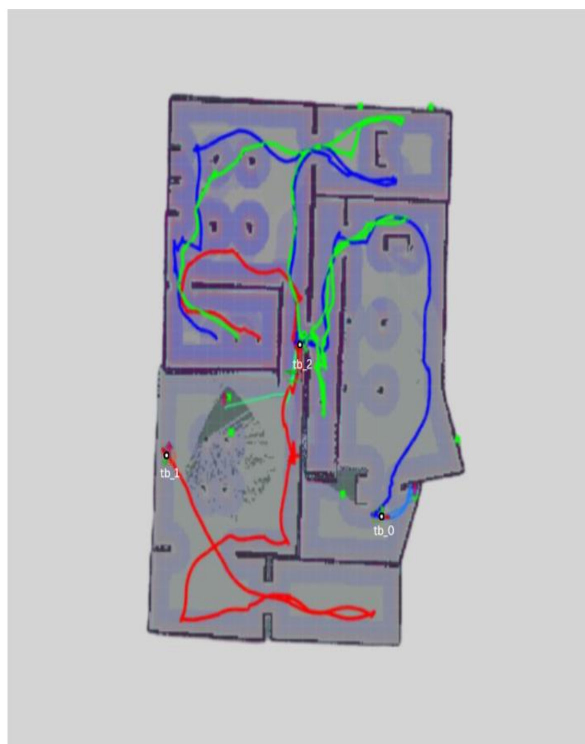

Fig. 8 Trial 1 output of proposed task allocation algorithm with coverage penalty parameter, Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

Fig. 9 Trial 2 output of proposed task allocation algorithm with coverage penalty parameter, Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

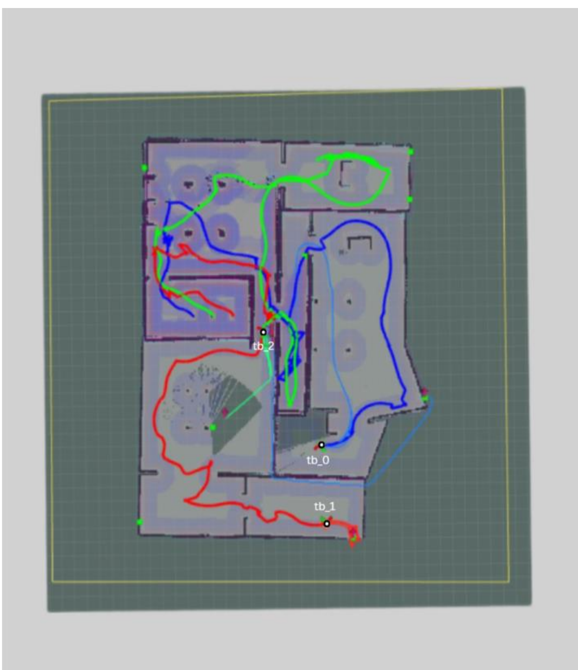

Fig. 10 Trial 3 output of proposed task allocation algorithm with coverage penalty parameter, Exploration travel path trajectories of robots: Robot 0 (blue), Robot 1 (red), and Robot 2 (green)

Overall, the comparative trajectory analysis confirms that integrating the coverage penalty parameter enhances exploration efficiency. The proposed strategy enables the robot team to cover a larger proportion of the environment while traveling a shorter cumulative distance, ultimately reducing energy expenditure and operational time. These improvements directly contribute to more effective multi-robot exploration and mapping in unknown environments.

7. Discussions as to the Effectiveness of the Proposed Method

Building on the comparative results presented in Figure 11, the analysis clearly demonstrates that the integration of the coverage penalty parameter into the dynamic task allocation framework yields measurable and consistent improvements in multi-robot exploration. The proposed method dynamically assigns tasks by evaluating multiple decision metrics-information gain, travel cost, and proximity penalties-allowing for balanced allocation decisions that minimize redundant traversal while maximizing environment coverage.

7.1. Efficiency

The inclusion of the coverage penalty parameter results in a notable reduction in both exploration time and travel distance compared to the baseline method. This efficiency gain is particularly advantageous in scenarios where operational time and energy resources are limited, such as autonomous field surveys or missions in resource-constrained environments.

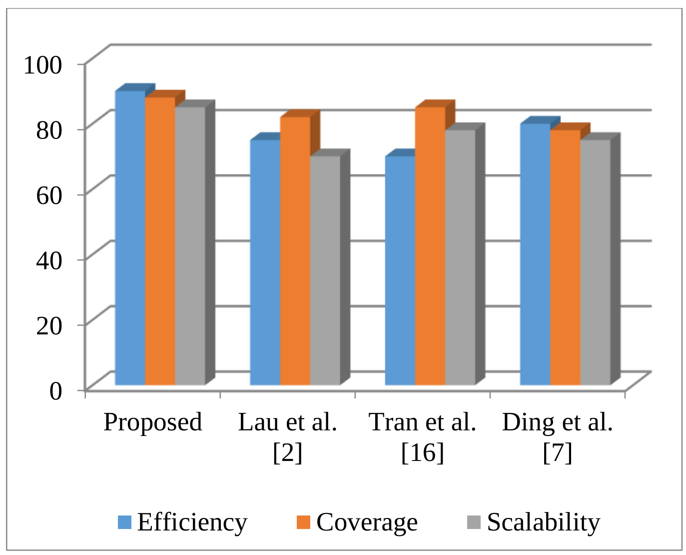

Fig. 11 Comparative analysis of the proposed method with state-of-the-art methods in the literature section

7.2. Coverage

The proposed technique can reduce inter-robot overlap over exploration areas, as representative task assignments that result in spatial overlaps will be discouraged. This is a welcome step to discover and map unknown areas, a needed benefit in surveillance, search and rescue applications, and applications in environmental monitoring, where the coverage should be comprehensive and thorough.

7.3. Scalability

The approach displays flexibility in different environments of different complexity, including those with rigid indoor design and those with disorderly and unstructured outdoor grounds. Such scalability allows the approach to be applicable to a wide scope of multi-robot systems and to be efficiently operative in both straightforward and extremely dynamic operation situations.

Additionally, the Z-score normalization procedure and the weighting of central indicators help prevent a situation where some parameter, e.g., distance, information gain, or the proximity penalty, prevails in the decision-making process. Such fair-mindedness increases the stability and rationality of the outcomes of the task allocation.

All in all, the experimental results indeed show that the coverage-enhanced dynamic task allocation algorithm (DP) works much better than the current strategies discussed in the literature review section by minimizing redundant travel, leading to better coverage efficiency, and still being scalable. Such benefits make the strategy an interesting approach to autonomous multi-robot exploration and mapping of unknown and unstructured environments.

8. Conclusion

After the overall analysis and discussion given in Section 6, the findings convincingly support that the proposed coverage-enhanced dynamic task allocation methodology can help solve the major limitations of the current practices in multi-robot exploration. Within a Z-score normalization framework, which integrates Information Gain Factor (IGF), Travel Cost (TC), and a Proximity Penalty (PP) parameter schema, the approach has the merit of balanced, adaptive, and computationally egalitarian decision-making. This would allow robots to divide and conquer evenly, reduce overlap of travels, and maximize space coverage. The effectiveness of the method is verified through simulation, where both the total exploration distance and the total completion time are decreased consistently, and the density of the coverage reaches an improvement in comparison to the reference algorithm (Umari et al. [28, 29]). These performance improvements prove the solidity of the suggested allocation strategy regarding time-saving, spatial optimizations, and the competence of operation.

The work is useful not only in terms of quantitative performance gains but also in that the framework reaches more strategically divided areas among the robots by explicitly incorporating spatial distribution constraints and proximity penalty in the allocation mechanism. Not only does it minimize energy use and extend working range, but it also increases the effectiveness of its mission deliverables within the sphere of application where resources are scarce, and decisions have to be made fast, e.g., environmental monitoring, disaster detection, industrial inspections, and search-and-rescue missions.

Although the simulation results are promising, there should be an important step towards their real-world validation. The future work will overcome sensor noise problems, communication latency, and changes in the dynamics of the environment, and extend the technique to be used in heterogeneous robot teams. Also, onboard adjustment of parameters in real time, combined with superior perception features, such as 3D LiDAR and/or high-resolution stereo vision, is to be considered to optimize mapping quality and situational understanding. To sum up, the Coverage-enhanced dynamic task allocation approach seems to be the most viable way of autonomous multi-robot exploration, due to its scalability, flexibility, and resource consumption. As it is refined even more and applied to actual situations, this framework can lead to large gains in the field of robotic exploration by providing capable, safer, and sustainable operations at an accelerated pace, more structurally intact, and less dislocated missions much sooner.

References

[1] Shengmin Zhao, and Seung-Hoon Hwang, “Exploration- and Exploitation-Driven Deep Deterministic Policy Gradient for Active SLAM in Unknown Indoor Environments,” *Electronics*, vol. 13, no. 5, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Billy Pik Lik Lau et al., “Multi-AGV’s Temporal Memory-Based RRT Exploration in Unknown Environment,” *IEEE Robotics & Automation Letters*, vol. 7, no. 4, pp. 9256-9263, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yizhen Yin, Hongjun Ma, and Xinkai Liang, “Improved RRT Autonomous Exploration Method Based on Hybrid Clustering Algorithm,” *Proceedings of 2021 International Conference on Autonomous Unmanned Systems*, pp. 416-425, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Ao Feng et al., “Efficient Autonomous Exploration and Mapping in Unknown Environments,” *Sensors*, vol. 23, no. 10, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Shayok Mukhopadhyay, Hassan Umari, and Koshish Koirala, “Multi-Robot Map Exploration Based on Multiple Rapidly-Exploring Randomized Trees,” *SN Computer Science*, vol. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Björn Lindqvist, Ali-Akbar Agha-Mohammadi, and George Nikolakopoulos, “Exploration-RRT: A Multi-objective Path Planning and Exploration Framework for Unknown and Unstructured Environments,” *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Prague, Czech Republic, pp. 3429-3435, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jun Ding et al., “An Improved RRT* Algorithm for Robot Path Planning based on Path Expansion Heuristic Sampling,” *Journal of Computational Science*, vol. 67, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Zeyu Tian et al., "Autonomous Exploration of RRT Robot based on Seeded Region Growing," *2020 39th Chinese Control Conference (CCC)*, Shenyang, China, pp. 3936-3941, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Xiaojing Tian et al., "Robot Autonomous Exploration and Map Building Method," *2023 International Conference on Robotics and Automation in Industry (ICRAI)*, Peshawar, Pakistan, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Zezhou Sun et al., "Frontier Detection and Reachability Analysis for Efficient 2D Graph-SLAM Based Active Exploration," *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Las Vegas, NV, USA, pp. 2051-2058, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Yusheng Yang et al., "Autonomous Exploration for Mobile Robot in Three Dimensional Multi-Layer Space," *16th International Conference Intelligent Robotics and Applications*, Hangzhou, China, pp. 254-266, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Lillian Goodwin, and Scott Nokleby, "A K-Means Clustering Approach to Segmentation of Maps for Task Allocation in Multi-Robot Systems Exploration of Unknown Environments," *Proceedings of the 2022 USCToMM Symposium on Mechanical Systems and Robotics*, pp. 198-211, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ankit Soni et al., "Multi-Robot Unknown Area Exploration Using Frontier Trees," *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Kyoto, Japan, pp. 9934-9941, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Kyung Min Han, and Young J. Kim, "Autoexplorer: Autonomous Exploration of Unknown Environments using Fast Frontier-Region Detection and Parallel Path Planning," *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Kyoto, Japan, pp. 10536-10541, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] S. Suruthi et al., "Evaluating Deep Learning Approaches for MRI Based Brain Tumor Detection," *2025 6th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, pp. 868-874, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Vu Pi Tran et al., "Frontier-Led Swarming: Robust Multi-Robot Coverage of Unknown Environments," *Swarm and Evolutionary Computation*, vol. 75, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Priyanka Ankireddy, S. Gopalakrishnan, and V. Lokeswara Reddy, "Gradient-Enhanced Focal-Pooling Vision Transformer with Adaptive Tuning for Robust and Accurate Vehicle Detection in Smart Environments," *Iran Journal of Computer Science*, 2025, [CrossRef] [Google Scholar] [Publisher Link]

[18] Nathanaël Randriamihamison, Nathalie Vialaneix, and Pierre Neuvial, "Applicability and Interpretability of Ward's Hierarchical Agglomerative Clustering With or Without Contiguity Constraints," *Journal of Classification*, vol. 38, pp. 363-389, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Xiangda Yan et al., "Multi-Robot Cooperative Autonomous Exploration via Task Allocation in Terrestrial Environments," *Frontiers in Neurorobotics*, vol. 17, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sheela Pitta, S. Gopalakrishnan, and S. Ravi Chand, "Securing WSN-IoT Networks using SwinAlert-GAN: A Deep Learning-based Intrusion Detection Framework," *2025 Third International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, Trichy, India, pp. 211-218, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] Lauren Bramblett, Rahul Peddi, and Nicola Bezzo, "Coordinated Multi-Agent Exploration, Rendezvous, & Task Allocation in Unknown Environments with Limited Connectivity," *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Kyoto, Japan, pp. 12706-12712, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] María Victoria Díaz et al., "Cooperative Indoor Exploration on Affordable Robots," *2022 Latin American Robotics Symposium (LARS), 2022 Brazilian Symposium on Robotics (SBR), and 2022 Workshop on Robotics in Education (WRE)*, São Bernardo do Campo, Brazil, pp. 235-240, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] Luiz Eugênio Santos Araújo Filho, and Cairo Lúcio Nascimento Júnior, "Multi-Robot Autonomous Exploration and Map Merging in Unknown Environments," *2022 IEEE International Systems Conference (SysCon)*, Montreal, QC, Canada, pp. 1-8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Kai M. Wurm, Cyrill Stachniss, and Wolfram Burgard, "Coordinated Multi-Robot Exploration using A Segmentation of the Environment," *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Nice, France, pp. 1160-1165, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ranjith Subramanian, Jesu Jayarin, and Arumugam Chandrasekar, "Hybrid Deep Learning Approach for 6G MIMO Channel Estimation and Interference Alignment HetNet Environments," *Traitement du Signal-International Information and Engineering Technology Association*, pp. 1951-1960, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] P. Jesu Jayarin et al., "Enhancing Cybersecurity in the Digital Age with Machine Learning for Threat Detection and Prevention," *2024 International Conference on Recent Advances in Science and Engineering Technology (ICRASET)*, B G Nagara, Mandya, India, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] V. Ragu, and P. Jesu Jayarin, "Detecting Flooding Attacks in Distributed Denial of Service Using Deep Neural Network Compared with Decision Tree," *Innovations In Thermal, Manufacturing, Structural And Environmental Engineering*, vol. 3267, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[28] Graeme Best, Jan Faigl, and Robert Fitch, "Online Planning for Multi-Robot Active Perception with Self-Organising Maps," *Autonomous Robots*, vol. 42, no. 4, pp. 715-738, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[29] C. Lakshmi, and P. Jesu Jayarin, "Design and Implementation of the Reconfigurable Area and Power-Efficient Steganography for Medical Information in MIMO-OFDM Channel Coding," *Wireless Personal Communications*, vol. 124, pp. 2271-2298, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] E. Minisha Devi et al., "Innovative IoT-Based Hybrid Electric Vehicle Charging System for Enhanced Efficiency and Sustainability," *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)*, Gobichettipalayam, India, pp. 1674-1679, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] N. Seenu et al., "Review on State-of-the-Art Dynamic Task Allocation Strategies for Multiple-Robot Systems," *Industrial Robot*, vol. 47, no. 6, pp. 929-942, 2020. [CrossRef] [Google Scholar] [Publisher Link]