1 Introduction

Deploying a team of autonomous mobile robots to explore unknown environments presents significant challenges [1, 2]. The primary goal is to gather accurate and high-quality information about the environment while minimizing the overall effort of the robotic team. Multi-robot coordination algorithms for online exploration have a wide range of real-world applications, including mapping, search and rescue operations, terrain exploration, etc. Multi-robot systems (MRS) offer a robust and fault-tolerant approach to online exploration by leveraging redundancy. However, selecting and designing an effective coordination strategy is crucial, as it determines the assignment of specific exploration objectives to individual robots while minimizing redundant efforts. Numerous researchers have proposed various solutions for online exploration.

Heterogeneous robots can collaborate by leveraging their unique capabilities, such as sensing and monitoring [3], while homogeneous robots can work together to overcome individual limitations through coordinated efforts [4]. Cooperation involves the simultaneous execution of tasks across a spatially distributed environment, including activities such as clearing pathways by opening doors, removing debris, extinguishing fires, providing first aid to casualties, or transporting them to safety. Cooperation is also studied in scenarios where robots must respond locally to prevent conflicts or collisions, such as in transportation systems on roads [], in the air [5], and in general robotic cooperation challenges [6]. In such scenarios, robots exhibit minimal interdependence, operating independently without needing assistance from others to progress while primarily ensuring they do not obstruct each other's paths.

We examine support in the context of mitigating various risks, such as fires, debris, etc, present in the environment. Such risks have been analyzed and formulated in different ways. For example, the probability of achieving specific performance levels in stochastic environments has been explored [7]. Some studies have focused on different risk measures, including coherent risk measures [8], such as conditional value-at-risk (CVaR) [9] and entropic value-at-risk (EVAR) [10]. Risk can also be defined using chance constraints [11], while game theory has been employed to address risks arising from uncertainties in an adversary's behavior [12]. Additionally, risk can be simply interpreted as the "cost" of traversal [13]. In this paper, we adopt the traversal cost approach to simplify our analysis.

In this paper, unlike [2, 14], we take a novel approach to exploration that differs from most existing methods []. Specifically, we focus on strategies that allow multi-robot systems (MRS) to expedite navigation and exploration by leveraging partial prior knowledge of the environment. Our goal is to determine the extent to which MRS can expedite environmental coverage using its sensors when it has prior knowledge of the environment's general layout. This objective is highly relevant to numerous real-world exploration challenges, as many scenarios involve environments with a known approximate structure. Examples include the exploration of underground spaces such as abandoned mines [15] and archaeologically significant tunnels like ancient catacombs [16], as well as inspection tasks such as assessing visually intact but potentially unstable buildings after an earthquake [17]. Consequently, similar to [18], this paper does not focus on the exploration of completely unknown environments. Instead, we present an efficient exploration strategy that utilizes prior knowledge of the environment's layout. In contrast to [18], where a single robot is employed and re-plans its schedule in response to partially or completely blocked paths—resulting in a single point of failure. Our approach incorporates multiple heterogeneous robots to enhance reliability and resilience. Additionally, in the single-robot approach, re-planning each time a partially or completely blocked path is encountered is time-consuming. To mitigate this issue, we introduce helpin robots into the environment to assist the primary exploration robots, thereby improving overall efficiency.

This paper introduces a novel multi-robot coordination strategy for exploring unknown environments. The key contributions of this work are as follows:

- We transformed the problem into a multiple traveling salesman problem $mTSP$ in the worst case of $O(n^3)$, where n is the number of nodes and utilized its solution to navigate the robot through the environment.
- Our approach generates significantly shorter paths compared to the state-of-the-art algorithm for test datasets with a large number of nodes by efficiently preventing multiple traversals of the same corridor and minimizing the need for re-planning in the presence of partially blocked paths. Therefore, the time required to cover the terrain is significantly reduced.
- Finally, our approach integrates the $mTSP$ solution with frontier-guided exploration, effectively eliminating redundant work on a global scale while ensuring comprehensive coverage of the environment by the robot's sensors.
- Extensive simulations using the ROS-based Gazebo simulator [] were conducted to evaluate the effectiveness of the proposed approach. Additionally, three state-of-the-art ($SOTA$) methods— [], (b) [], and (c) []—were re-implemented for heterogeneous autonomous mobile robots. These approaches were compared with the proposed algorithm, and the results show that the proposed approach outperforms all three SOTA methods.

2 Related Work

Autonomous exploration involves navigating and mapping unknown environments while optimizing metrics such as overall travel distance [] and time [19]. A review of the literature reveals that various exploration strategies have been proposed [], including graph-theoretical methods [] and frontier-based approaches []. In [20], authors introduced the Wave-front Frontier Detector (WFD), which employs a depth-first search approach, allowing each robot to scan only its assigned area. However, although WFD avoids full-map scanning, its performance deteriorates considerably as the exploration area grows larger [21]. To address this issue, authors in [20] developed the Fast Frontier Detector (FFD) method. The FFD method improves efficiency by significantly reducing the search scope, focusing only on areas containing boundaries. However, due to its limited search space, FFD can only run continuously in the background.

In [22], authors introduced the frontier-based approach, which remains one of the most widely used methods for exploration. A frontier is defined as a collection of regions located at the boundary between explored and unexplored areas [23]. Over time, the application of these methods has evolved from single-robot to multi-robot systems. Additionally, various frontier-based techniques have been employed for edge detection in image processing [24]. However, when applied to high-dimensional environments, the complexity of the required processing methods increases significantly [].

Rapidly exploring Random Trees (*RRT*) [25, 26] is a fast probabilistic planning method capable of extending to multidimensional spaces. Notably, *RRT* is a probabilistically complete method [27] that ensures thorough exploration and full map coverage. The algorithm constructs a tree structure starting from an initial point, expanding in a direction determined by randomly selected points within the planning space. Based on *RRT*, an opportunity-constrained sub-path can be generated from the starting position to the target [28]. The *RRT* path planning algorithm can also be applied to identify frontier points in a dynamically evolving map. [29] introduced the concept of utilizing *RRT* for frontier point detection. Frontier points located at the map's boundary are typically selected as target points for the robot. Moreover, since the *RRT* algorithm is inherently biased toward unexplored areas [29], it efficiently identifies frontier points, accelerating the exploration process.

The *RRT* scheme can also be viewed as a Monte Carlo method. When the sampling search space is uniform, the expansion probability of an existing state is proportional to the size of its Voronoi region. Since the largest Voronoi region corresponds to the leading edge of the search, the tree naturally extends toward large unexplored areas. However, as robots move toward frontiers, they often explore the same regions multiple times due to the inherent randomness of the generated paths [24]. To address this issue, Dynamic Domain RRT (*DDRRT*) refines the nearest-neighbor search by considering only nodes within a specified distance threshold from the random sample [30]. *DDRRT* approach reduces the search volume around expandable nodes while decreasing the selection probability of frontier points near obstacles. Although *DDRRT* effectively mitigates the challenges posed by narrow passages, its performance is highly sensitive to the chosen threshold value.

The exploration approaches mentioned above operate without prior knowledge, meaning they do not utilize background information or assumptions about the environment's structure. Only a few methods integrate prior knowledge to enhance decision-making for determining the next movement. For instance, [31] proposes an approach that incorporates knowledge from previously explored environments into a cooperative mapping and exploration system for multiple robots. Similarly, [32] leverages previously explored areas to predict future loop closures, thereby guiding exploration more efficiently. Other methods utilize semantic information [33] or environmental segmentation [34] to optimize target location assignments, gaining significant attention in multi-robot exploration.

Additionally, authors in [35] introduce a multi-robot target assignment framework inspired by market economy principles. Their approach evaluates potential target location sequences and assigns tasks using single-item first-price sealed-bid auctions, a technique also employed by [36] for task allocation. In contrast, [37] utilizes the Hungarian method [38] to optimally assign open frontier cells to robots, particularly focusing on aligning robot trajectories when their starting positions are unknown.

In [34], authors propose a coordination strategy where robots are assigned exploration targets based on segmented regions of the environment, aligning with the spatial semantic hierarchy concept introduced by [39]. These semantic and segmentation-based approaches [34] demonstrate that assigning robots to unexplored segments, rather than individual frontier points, results in a more balanced distribution across the environment. Authors in [40] further analyze various exploration strategies and propose heuristics to improve their overall efficiency.

In this paper, we explore methods to accelerate robotic exploration by leveraging prior environmental knowledge. Our focus is on application scenarios where the approximate layout of the environment is known in advance. While our approach is related to coverage techniques [41, 42], we do not assume a predefined grid map or polygon for viewpoint planning. Unlike purely graph-based coverage techniques [43], our method incorporates local exploration strategies that consider the surroundings of graph nodes.

Patrolling methods [44, 45] emphasize multi-robot coordination and global exploration strategies, whereas our approach integrates both global and local strategies for more efficient exploration. The use of abstracted map information has been explored in other navigation problems. For instance, authors in [46] utilize hand-drawn sketch maps to help robots infer qualitative spatial relationships for navigation, while authors in [47] employ schematic maps for similar purposes. In contrast to [47], our method exploits topo-metric information in the form of a graph but without requiring the user to specify a predefined path. Instead, global environment information is used to compute an optimal exploration strategy upfront, which then guides robots through the environment efficiently.

Our approach is also related to the work of [48] and [49], both of whom formulate multi-robot coordination in exploration as a Multiple Traveling Salesman Problem ($mTSP$). Similarly, we also employ a ($mTSP$)-based formulation on a user-provided graph but enhance it by integrating local exploration strategies at individual locations.

3 Problem Setup

We consider a scenario in which a team of autonomous robots must explore an entire map, starting from their respective initial positions. The objective is to ensure that the robotic team thoroughly explores every region of the map. However, unlike traditional exploration problems where each robot operates independently, we specifically focus on a cooperative setting in which the presence and actions of other team members have a direct impact on the overall traversal cost. In this cooperative framework, the movement of each robot through the environment is influenced by the “support” provided by its teammates. The term “support” refers to how the presence of other robots along specific paths can modify the traversal effort, potentially reducing or increasing the cost of movement based on factors such as shared workload, environmental adaptation, or resource sharing.

3.1 Graph Representation

The environment is modeled as a connected undirected graph

$$G = (V, E),$$

where $V = \{v_0, v_1, \ldots, v_N\}$ denotes the set of vertices (locations) and $E \subseteq V \times V$ denotes the set of edges representing feasible movements between locations. Vertex v_0 is a common depot from which all agents start.

Each edge $e \in E$ is associated with a base traversal cost $d_e > 0$. A subset of edges $E_r \subseteq E$ are classified as *risky edges*.

3.2 Risky Edges and Probabilistic Penalty

For each risky edge $e \in E_r$, traversal can occur in one of two modes:

- **Solo traversal**, with cost d_e^{solo} and failure probability p_e^{solo}.
- **Cooperative traversal**, with cost d_e^{coop} and failure probability p_e^{coop},

where

$$d_e^{\text{coop}} \leq d_e^{\text{solo}}, \quad p_e^{\text{coop}} < p_e^{\text{solo}}.$$

A failure during traversal incurs a penalty cost $P > 0$. Thus, the expected traversal cost of edge e is given by

$$\mathbb{E}[c_e] = d_e + p_e \cdot P.$$

Each risky edge $e = (u, v) \in E_r$ is associated with a supporting vertex $s_e \in \{u, v\}$ and a minimum cooperation requirement $k_e \geq 2$. Where k_e is the minimum number of agents required to cooperate in order to safely traverse a risky edge e.

3.3 Agents and Movement Dynamics

Let $A = \{a_1, a_2, \ldots, a_M\}$ denote the set of M agents. All agents start from the depot v_0 at time $t = 0$. Time is discretized as $t = 0, 1, \ldots, T$. At each time step, an agent occupies exactly one vertex and can either move to an adjacent vertex or remain stationary.

3.4 Movement and Cooperation Constraints

Let $p_i(t) \in V$ denote the position of agent a_i at time t.

3.4.1 Movement Feasibility Constraint

An agent may only move along existing edges:

$$p_i(t+1) \in \{p_i(t)\} \cup \mathcal{N}(p_i(t)),$$

where $\mathcal{N}(v)$ denotes the set of neighboring vertices of v.

3.4.2 Cooperation Constraint

For a risky edge $e = (u, v) \in E_r$, cooperative traversal is enabled only if

$$|\{a_i \in \mathcal{A} \mid p_i(t) = s_e\}| \geq k_e.$$

If this condition is not satisfied, traversal is considered solo and incurs a higher failure probability.

3.5 State Definition

The global system state at time t is defined as

$$s_t = (p_1(t), p_2(t), \ldots, p_M(t), \mathcal{V}_t)\,,$$

where $\mathcal{V}_t \subseteq V$ is the set of vertices visited up to time t.

Each agent has access only to partial and local observations derived from s_t, making the problem decentralized and partially observable.

3.6 Coverage Constraint

All vertices must be visited at least once:

$$\bigcup_{t=0}^{T} \mathcal{V}_t = V.$$

3.7 Objective Function

The objective is to learn decentralized policies $\pi_1, \ldots, \pi_M$ that minimize the expected cumulative cost:

$$\min_{\pi_1,\ldots,\pi_M} \mathbb{E}\left[\sum_{t=0}^{T}\sum_{i=1}^{M}\left(c^i_{\text{travel}}(t) + p^i_{\text{fail}}(t)\cdot P\right)\right],$$

where $c^i_{\text{travel}}(t)$ is the traversal cost incurred by agent a_i at time t, and $p^i_{\text{fail}}(t)$ is the failure probability associated with the chosen action.

4 Methodology

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