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Market-Based Collaborative Exploration and Mapping of an Unknown Indoor Environment

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Abstract **-** Autonomous exploration and mapping is an important topic in the research and development of robotics intelligence. In this paper, we present an efficient, coordinated multi-robot exploration. Each robot uses a hybrid exploration strategy to exploit the advantages of global and local explorers, namely frontier-based and Rapidly exploring Random Tree. Next, to coordinate robots, we propose a strategy that is inspired by both market and pheromone-based approaches to increase the information gain at each step while reducing the exploration cost. The proposed method is evaluated with a 2D simulation setup through several experiments. Compared with the existing methods, the proposed approach yields a more efficient search by reducing overlap between robots.
Keywords**:** Autonomous Exploration and Mapping, Coordination, Multi-robot exploration, Task allocation

1. Introduction

Mobile robots can be deployed in various robotics missions [1], including search and rescue [2], disaster management, environmental protection [3], and planetary exploration [4]. Challenging environments can be dangerous to human operators [5, 6]. To deploy an autonomous robot in these areas, it is essential to equip them with an exploration and mapping strategy, which is a fundamental problem for mobile robots. One of the main challenges is to reduce exploration time while increasing the map quality [6, 7]. The collaborative exploration with multiple robots brings several advantages, including increased robustness [8], reliability [9], and reduced overall task completion time [10]. However, a multi-robot system brings new challenges, including the design of an efficient communication strategy among robots [11], computation complexity, avoiding conflicts such as exploring the same area by multiple robots [12], and integration of maps generated by multiple robots [13]. This paper is aimed at presenting a reliable, collaborative exploration strategy to minimize the overlap among robots exploring areas.

In a multi-robot structure, each single robot must integrate motion planning, mapping and exploration techniques to explore an unknown environment effectively [14]. The two most well-known categories for single robot exploration strategies are frontier-based and sampling-based approaches. In the former, robots extract frontiers (the border between known (explored) and unknown areas) and move towards them sequentially. Usually, each time that a robot reaches a frontier, a frontier detection algorithm will be applied to detect the next frontiers [15]. In this paper, we detect frontiers based on the Fast Frontier Detector (FFD) technique [16] to limit the search area and increase exploration speed. We use an incremental frontier detection technique to find new frontiers and update the target frontiers while moving toward the initially selected frontier. While frontier-based approaches guarantee the full coverage of the environment, they are slow and computationally expensive [17]. The sampling-based approaches find the next position to be explored faster than the frontier-based methods [17]. One of the most well-known sampling-based approaches is Rapidly exploring Random Tree (RRT), in which a randomized data structure, known as a tree, is expanded from the starting point (the robot's location) and moves to a frontier point [18]. This tree expands in random directions with a bias toward the unknown areas of the environment. [19] and [20] used RRT as the only frontier detector. However, RRT does not utilize an optimization function, and since it grows randomly, it is prone to get stuck locally or perform an inefficient exploration [17]. Hybrid exploration strategies enhance the efficiency of exploration and mapping by creating a balance between exploration and exploitation. Discovering and identifying unknown portions of an environment can be considered as a reward for exploration algorithms. Frontier-based techniques, as an exploitation technique, maximize short-term rewards at each step, which does not necessarily lead to an acceptable long-term reward. On the other hand, RRT could increase the long-term reward by adding randomness to the exploration [21]. In this project, the frontier-based algorithm and RRT are used as the global and local explorers, respectively.

Multi-robot exploration can be considered as a group of single robots equipped either with a coordination strategy or not. The two ends of the coordination strategy spectrum are centralized and decentralized approaches [22]. The fully centralized approaches generate optimal solutions by considering information gathered by all robots. However, they are computationally expensive and are usually not developed well for dynamic environments [22]. On the other hand, in a decentralized method, robots are fully independent in making decisions on their own. Unlike centralized approaches, these methods are robust to changes in the environment. The main disadvantage of these methods is that they may result in suboptimal solutions [12]. The fundamental aspect of the coordination strategies, either centralized or decentralized, is task planning, in which the two problems of task decomposition and task allocation are studied. Task planning is key to increasing exploration efficiency by allocating frontiers efficiently to robots in a way to avoid overlap as much as possible. Several task allocation strategies for different purposes have been studied, including distributed constraint optimization, dynamic programming, market-based approach, and swarm intelligence [23, 24, 25, 26]. Among all the current methods, the market-based approach is one of the most suitable strategies for task allocation because it is highly efficient and can be easily implemented. Market-based approaches have elements of both centralized and decentralized methods such that computation is distributed among all robots while a central unit allocates tasks to all robots. [20] used RRT and market-based approaches as exploration and coordination strategies, respectively, and they have studied multi-robot exploration as an optimization problem. RRT is used as the only exploration strategy which may not find the optimal global solution.

The present study introduces a new market-based approach, enhanced with a bioinspired technique. The anti-pheromone idea comes from the ant colony optimization technique: when ants move, they mark their path with a chemical pheromone [27, 28]. Ants move toward paths with a stronger pheromone. [25, 29] used the opposite idea as the only task allocation mechanism to prevent overlap between areas covered by different robots. [30] has used market-based auction with the pheromone map to control the movement of aerial vehicles to explore non-visited areas while handling network connectivity issues. The current paper combines the anti-pheromone and market-based task allocation techniques along with the hybrid exploration strategy to maximize autonomous exploration efficiency by reducing the overlap between robots. The proposed task allocation module in this paper is robust against the initial distribution of robots and prevents overlapping. Another advantage of the proposed method is that it is robust against robot failures by adapting to variable numbers of robots during a mission. To evaluate the performance of the proposed approach, simulation environments are designed and programmed in Python. In short, the novelty of this paper is applying a hybrid exploration strategy with an enhanced market-based task allocation algorithm, which results in safe and efficient exploration of the environment such that the overlap between robots is minimized and the exploration is efficient.

2. Methods

An occupancy grid map is used to represent an indoor environment that robots need to explore. A map is divided into n small grid cells, and each robot occupies a cell. There are three types of cells in an occupancy grid map: known free, known occupied (e.g. objects or wall) and unknown, represented with the probabilities of $p(cell(i)) < 0.5, p(cell(i)) > 0.5, p(cell(i)) = 0.5$ where $1 \leq i \leq n,$ respectively. In a multi-robot system, each robot creates a local map and extracts frontiers based on, e.g., Light Detection and Ranging (LIDAR) sensor measurements. The local maps, generated by different robots, are merged to form a global map. Then all frontiers are saved in a common list known as the global frontiers. When a robot moves, its sensors can detect new areas, so the global frontiers list gets updated constantly via the detector module, followed by the clustering and filtering module. The K-means clustering algorithm [31] is used to cluster the detected frontiers. The centroid of some clusters may lie on unknown cells, and thus it is not clear whether the centroid is free or occupied. If a centroid is in an occupied cell, the robot could hit an obstacle, which reduces safety significantly. Even if the centroid is in the free space, it may not be reachable, i.e., there may not be a feasible path that the robot can take to reach the centroid. Thus, the filtering module is required to remove the centroids which are in the unknown cells. The task allocation module distributes the filtered frontiers between robots. Then, the exploration module defines the next position that a robot should move to, referred to as an exploration node, by choosing between the global exploration node provided by the task allocator module or the local exploration node by the local explorer. RRT, as the local explorer, is used to add randomness to improve the long-term reward. The robot expands a random tree in its local neighbourhood until the last node lies in an unknown cell. Since it is not guaranteed that the selected point lies in the free space, the node before the last one is considered the exploration goal. This modification increases the safety of the exploration significantly. Then each robot uses the motion planning module to generate a path toward the exploration node based on the known map [32]. We use A* as the planner to provide an obstacle-free path in the partially known environment map [33]. The Bayesian update is used to generate an occupancy grid map during the exploration [34]. Since the focus of this paper is on exploration and task allocation, we assume that the Simultaneous Localization and Mapping (SLAM) [35] is well established and can be implemented successfully. The task allocator's duty is to allocate the best possible frontier to each robot. To reach this goal, the task allocator needs to solve an optimization problem considering the utility function. To evaluate each frontier for a robot, the following terms are considered.

1) Cost (C): The cost is defined as the distance between the current robot's position and the frontier position, represented by subscripts c and f, respectively in Equation (1). The Euclidian distance is used in this paper to approximate the cost. The obtained results show that the approximation leads to a proper solution while it is not computationally expensive.

$$C = \sqrt{\left(x_f - x_c\right)^2 + \left(y_f - y_c\right)^2} \,. \tag{1}$$

2) Information Gain (IG): The information gain is considered as the predicted information that a robot would gain if it were located at a specific frontier. However, it is not possible to evaluate the exact information gain value. A circle with the LIDAR range radius is formed at each frontier, and the number of unknown cells lying in this circle is considered as the information gain value. In the single robot case, the robot moves toward the frontier with the maximum information gain and the minimum cost, defined by the utility function as follows.

$$U_N = \alpha IG_N - \beta C_N, \tag{2}$$

where α and β weigh the importance of the information gain and cost respectively. The information gain and the cost have different orders of magnitude, so they are normalized between 0 and 1. In order to increase the safety and efficiency of exploration, frontier re-sampling takes place when the robot reaches half of the path length to the initially chosen frontier.

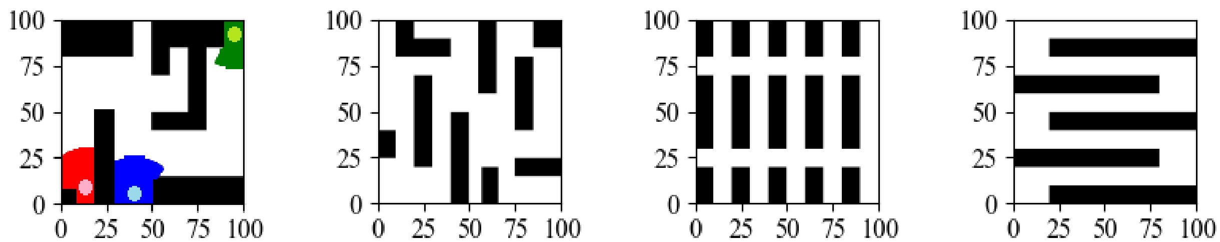
The utility function is further modified for the multi-robot system. In this paper, for multi-robot exploration, the task allocator module is an enhancement of the simple market-based approach modified by a bio-inspired technique. In the simplest market-based approach, a set of items (frontiers) is offered by an auctioneer, and the participants (robots) submit their bids (the cost of visiting frontiers) for each item (frontier). The task allocator tries to maximize the global utility function by distributing tasks among all robots in a way to reduce total overlap between robots. The utility function introduced in Equation (2) can be used by the task allocator. However, using this simple optimization function could give rise to several problems. There is a possibility that the selected frontier does not lie on the local map of the robot, and there is no clear path to this point, even given the global map. To solve this issue, the frontiers outside of the local map of each robot are penalized in the utility function with a parameter, shown by c. The value of c for the frontiers inside the local map of the robot is 0. If the frontier is outside of the local map of a robot, it is penalized by a constant value of 2. Finally, a matrix consisting of all c values is normalized between 0 and 1. The anti-pheromone mechanism, shown by p in the utility function, is introduced to encourage robots to move toward unseen areas by avoiding exploring the already explored areas. To achieve this, the percentage of the area which is covered in the neighbourhood of frontiers is compared, and the frontiers that are in locations with a larger percentage of explored areas are penalized more. The value of p for each frontier is equal to the number of free cells that are in 0.75 of the lidar range. A matrix including all p values is normalized between 0 and 1. To avoid the possibility of assigning two or more close frontiers to robots which reduces the overall efficiency, in this paper, each robot is assigned an identification number (ID). The robot with the smallest ID is chosen as the leader, and the frontier with the highest utility is assigned to the leader. The cost of moving to the frontiers near the selected frontiers is increased for other robots by a factor of 5. Thus, the tendency to move to adjacent areas is reduced significantly. In summary, considering the case, there are N robots and M frontier, the task allocator calculates the utility of all M frontiers for the first robot and the frontier with the highest utility would be assigned to the first robot. Then the values of $(M-1)$ frontiers are updated for the second robot, and the frontier with the highest utility goes to the second robot again. This process continues until all robots have their own specific frontier. The modified utility function is as follows

$$U_N = \alpha IG - \beta C - \lambda c - \gamma p, \tag{3}$$

where c and p are weighted by λ and γ, respectively.

3. Results and Discussion

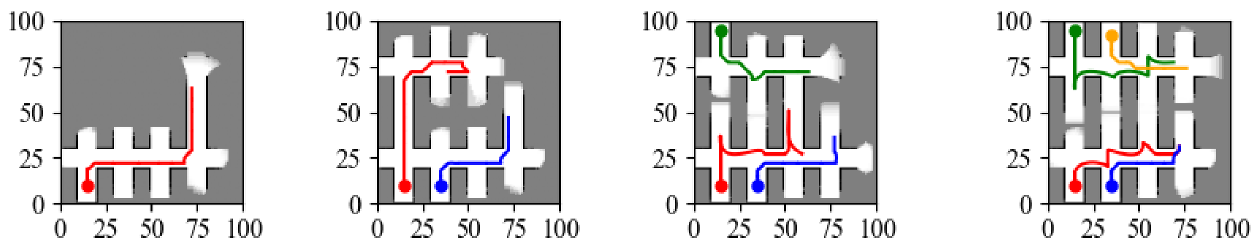
The proposed coordinated exploration strategy is studied on mobile robots equipped with LIDAR sensors. Figure 1 illustrates different indoor simulation environments used for evaluation. Each map is 10^4 m^2 with equal height and width, while each robot's LIDAR range is 20 meters with 360 degrees field of view.



a b c d

Figure 1. Static simulation environments, including maps a,b,c, and d. The initial location of three robots and their LIDAR range is represented in sub-figure (a).

The coefficients in Equation (3) are set to $\alpha = 0.8$, $\beta = 2$, λ and $\gamma = 1$. These parameters are defined based on the multi-robot exploration efficiency and several experimental tests. The main evaluation metric in this paper is efficient map coverage. The number of robots in a multi-robot system plays an important role in the efficiency of the exploration. Figure 2 shows increasing the number of robots increases the coverage of the map significantly in the same exploration time, considering the same speed for all robots.



a. One robot b. Two robots c. Three Robots d. Four robots

Figure 2. Exploring map c with different numbers of robots while exploration times are the same.

Figure 3 shows the average exploration time required to cover 50% of the map c for different numbers of robots. It is clear there is no considerable difference between the mean exploration time of three and four-robot scenarios. Therefore, increasing the number of robots from three to four will not improve the exploration's efficiency significantly, and three is considered as the optimal number of robots in our simulation environments.

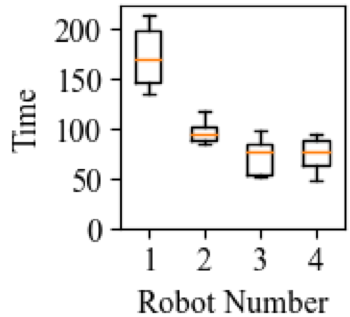


Figure 3. Exploration time required for 50% of map coverage versus the number of robots.

Figure 4 illustrates the maps created by a group of three mobile robots when about 90% of the map is explored. The path each robot followed during the exploration is shown. It is clear there are few overlaps between robots' paths. If there is an overlap between robots' paths, it is because the robot has fully explored its own local environment, and it is going to help other robots to complete the global map.

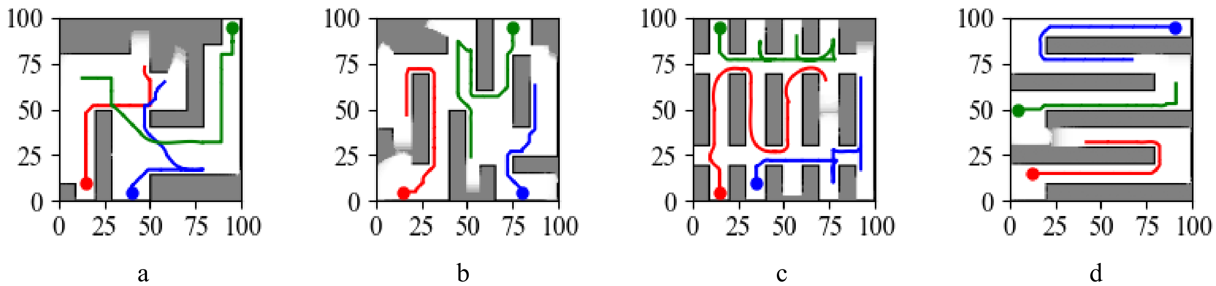


Figure 4. Exploration of four static simulation environments with different structures by three robots.

We also studied the effects of the anti-pheromone mechanism in the proposed coordination strategy. Figure 5 compares the result of exploration with anti-pheromone ($\gamma > 0$) and without anti-pheromone ($\gamma = 0$) , with three robots. Initially, because of the initial distribution of robots, the environment is not very well divided between robots, and there are some overlaps between their local maps. However, with the anti-pheromone mechanism, after a while, this issue is solved. Considering Figure 5 a and b, it could be concluded that the anti-pheromone mechanism reduces the exploration time required to cover 90% of the map since there are more overlaps between green and red robots in subfigure b. Moreover, the exploration time for Figure 5 a and c is the same, but the map coverage is less in subfigure c.

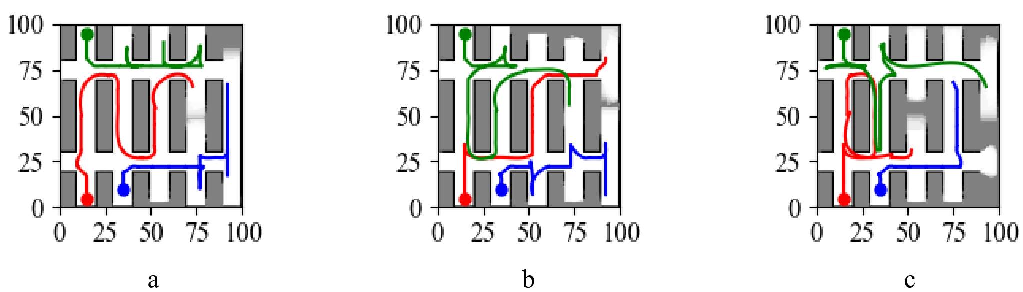
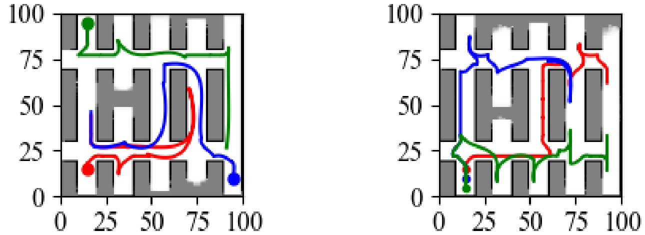


Figure 5. Effects of the anti-pheromone mechanism: a. with anti-pheromone mechanism and 90% map coverage, b. without anti-pheromone mechanism and 90% of coverage; the exploration time is more than (a), c. without anti-pheromone mechanism and the same time as (a).

Figure 6 examines the robustness of the proposed algorithm to the initial distribution of robots. Considering Figure 6 b, in the beginning, all robots are located very close to each other. However, after a while, they are distributed evenly in the environment. This shows that the exploration process is not dependent on the initial location of the robots, and robots are able to explore an environment efficiently.



a b

Figure 6. Comparing effects of the initial distribution of robots: a. different initial locations, b. same initial location

Finally, Figure 7 shows that even if one robot fails, as shown by the green colour, the exploration task is not stopped, and other robots continue to communicate and finish the task because of the decentralized properties of the proposed coordinated exploration strategy.

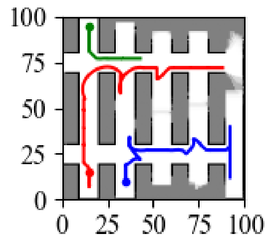


Figure 7. 90% of map coverage after one of the three robots fails.

4. Conclusion

In this project, an effective coordinated exploration strategy is analysed. The coordination strategy is mainly inspired by the market- and pheromone-based approaches to reduce the overlap between robots as much as possible. Moreover, the exploration strategy is a combination of frontier-based and RRT as global and local explorers, respectively. The exploration task is distributed among explorers in a way to benefit from both exploration and exploitation advantages. The main objective of the suggested approach is to increase the map coverage while reducing the exploration cost. The effectiveness of the method is studied through several simulations, and results prove that this strategy can explore an environment efficiently with minimum overlap. In future works, we will study the effect of learning-based strategies to improve exploration efficiency further.

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