ON PARAMETERS SETTINGS IN MULTI-ROBOT EXPLORATION STRATEGIES

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Abstract: **This paper presents a discussion about influence of parameters settings in decision making strategies in multi-robot exploration of unknown environment that are based on the task-allocation problem formulation. We aim to point out hidden pitfalls of the task-allocation problem formulation of the robotic exploration and show how different local strategies of the goal assignment can influence the overall exploration performance. In the presented evaluation study, we consider well established exploration strategies based on frontier-based goal candidates determination methods. A discrete event based simulator of the multi-robot exploration is used to control all the hidden issues like the local robot planner, which can affect the performance of the exploration significantly. This evaluation framework allows to study behaviour of the algorithms for different parameters and evaluate the system performance statistically, and therefore, the found insights are based on thousands of trials.**

Keywords: **multi-robot exploration**

1. Introduction

Multi-robot exploration can be defined as a problem to create a map of the given unknown environment by a group of mobile robots each equipped with a sensor system to perceive its surroundings. Such a map can be further used for planning, support localization, or to find objects of interest located in the environment. Thus, the exploration task can be also considered as a problem of data collection from unknown environment and different objective functions can be followed. The motivation for the studied exploration strategies is the search and rescue mission, where the aim of the exploration is to provide a map of the environment as quickly as possible and thus the time to create a map of the whole environment is the main objective function considered in this paper.

The fundamental approach to robotic exploration is Yamauchi's frontier based method [1] introduced in 1997 for a single robot that has been extended to multi-robot missions in [2]. The approach uses a grid map representation of the environment and new sensor measurements are integrated in an occupancy grid using Bayes rules [3]. The probability a cell is occupied is thresholded into three possible states: *occupied*, *free*, and *unknown*. The central point of this approach is to iteratively assign new navigation goals to the robots in the-next-best view manner, while the goal candidates are the so-called frontier cells, i.e., freespace grid cells that are incident with an unknown cell. Thus, frontiers represent an area between the already explored and unexplored parts of the environment.

Yamauchi's assignment of the goals is a greedy strategy that utilizes the distance of the robots to the frontiers and the closest frontier is assigned to each robot. Although this method works in practice, there are many approaches improving this greedy assignment that consider additional constraints like localization and expected areas to be covered [4, 5, 6, 7, 8, 9, 10].

In this paper, we focus on the multi-robot exploration strategies that are based on the task-allocation problem formulation [11]. The decision making process in the exploration is considered as an iterative procedure consisting of the navigation of the robots to the actual goals while new sensor measurements are integrated to the occupancy grid. After selected navigation steps, frontiers are determined in the current map, new goal candidates are selected from the frontiers, and for each robot a next goal is assigned from the goal candidates. Then, the robots are navigated to the goals and the procedure is repeated until all reachable frontiers are covered.

The algorithm how new goal candidates are determined together with the algorithm for their assignment to the robots is called the exploration strategy in this study. The performance of the exploration depends on these two algorithms as it has been shown in our previous work [12, 13, 14]. Besides, it also depends on the frequency of the replanning and one can expect that a more frequent replanning improve the performance. However, it is not necessarily the case if the assignment of the goals is not stable and robots can oscillate. This has been reported even for a single robot exploration and utility based evaluation of the goal candidates selection using expected area to be covered from the particular candidate [8].

In addition to a comparison of the exploration strategies and frequency of the replanning, we study the following aspects of the exploration procedure and their influence to the performance of the mission. First, as we aim to minimize the exploration time, we discuss pitfalls of the estimation of the robot travel time by a traveled distance. Second, we study the performance of the strategies in the exploration missions, where it is required all the robots return to the starting positions (depot), e.g., because of the requirement to collect high quality images of the explored areas that cannot be transmitted remotely [15]. Finally, we investigate performance of the exploration in the context of the decision making for the robots without assigned goals, e.g., due to a lower number of goal candidates than the number of robots.

The paper is organized as follows. Assumptions and the multi-robot exploration framework used for the evaluation is described in Section 2. A brief description of the evaluated exploration strategies is presented in Section 3. Hidden pitfalls of assumptions and approximations in the task-allocation based multi-robot exploration are discussed in Section 4. Evaluation methodology and results of the performed comparisons are presented in Section 5 together with a discussion of the proposed hypotheses and found insights. The concluding remarks are depicted in Section 6.

2. Problem Statement

The multi-robot exploration is studied as a centralized approach for a homogeneous group of m mobile robots that are equipped with an omnidirectional sensor with the sensing range ρ. The control architecture for the exploration mission is implemented as an iterative procedure where new sensor measurements are integrated into the common map. After a selected number of navigation steps, new goal candidates are determined and selected goals are assigned to the robots. Let the occupancy grid be $\mathcal{O}cc$, the set of robots be $\boldsymbol{R} = \{r_1, \ldots, r_m\}$, then the procedure can be summarized as follows:

1) Initialize the occupancy grid $\mathcal{O}cc$ and the initial robot plans to $\mathcal{P} = (P_1, \ldots, P_m)$, where $P_i = \{\emptyset\}$.
2) `Repeat`
   a) Navigate robots towards their goals according to the plans $\mathcal{P}$;
   b) Collect new measurements with the range ρ to the occupancy grid $\mathcal{O}cc$;

   `Until` **replanning condition is meet**.
3) Update a navigation map $\mathcal{M}$ from the current occupancy grid $\mathcal{O}cc$.
4) Detect all frontiers $\mathcal{F}$ in the current map $\mathcal{M}$.
5) **Determine goal candidates $\boldsymbol{G}$** from the frontiers $\mathcal{F}$.
6) `If` $|\boldsymbol{G}| > 0$ **assign goals to the robot**
   - $(\langle r_1, g_{r_1}\rangle, \ldots, \langle r_m, g_{r_m}\rangle) = \mathrm{assign}(\boldsymbol{R}, \boldsymbol{G}, \mathcal{M})$, $r_i \in \boldsymbol{R}$, $g_{r_i} \in \boldsymbol{G}$;
   - Plan paths to the assigned goals (as sequences of grid cells) $\mathcal{P} = \mathrm{plan}(\langle r_1, g_{r_1}\rangle, \ldots, \langle r_m, g_{r_m}\rangle, \mathcal{M})$;
   - Go to Step 2.
7) Stop all robots or navigate the robots to the depot (all reachable parts of the environment are explored).

Notice, the navigation (Step 2) can be repeated until a robot reaches its goal or whenever an assigned goal will no longer be frontier, e.g., a surrounding unknown area becomes explored. Based on this replanning condition, we can distinguish two variants of the exploration strategies. The first variant is called *goal replanning* (GR) and the second variant is called *immediate replanning* (IR). It is clear that the second variant is more computationally demanding as surrounding cells of the frontier can be explored once the robot moves towards the goal about a distance equal to the size of the grid cell, e.g., 0.05 m that is used for the results presented in this paper; hence, new goals and assignment have to be determined as quickly as possible.

The performance of the exploration depends on the replanning period (for example see [13]) and thus it also depends on the speed of the robot and available computational resources. Therefore, we consider a discrete event based simulator, where the robot motion is restricted to traverse single grid cell per one simulation step, which avoid influence of the available computational power and it allows to evaluate performance of computationally demanding exploration strategies independently on the used hardware.

Furthermore, we consider the robots have omnidirectional wheels and can move in arbitrary direction in the grid. However, distances between the robots and goal candidates are determined using the Distance Transform (DT) algorithm [16] and paths are then simplified by simple ray shooting procedure [13]. The evaluation criterion can be based either on the maximal traversed path L_{max} or on the required number of the simulations steps k.

The used exploration strategies are based on the task-allocation algorithms described in the following section. The complexity of the assignment depends on the number of goal candidates. For a high number of candidates, the task-allocation can be computationally demanding, e.g., using the TSP distance cost introduced in [12], therefore we rather consider representatives of the frontiers, from which the frontiers can be covered. Notice, a less number of goal candidates provides better performance of the whole exploration mission than using all frontiers. For a more details see our results in [14], where we compare different task-allocation strategies accompanied by several methods of the goal candidates determinations. The used method of the goal candidate determination is described in Section 3.2.

3. Considered Exploration Strategies

3.1. Task-Allocation Strategies

The following task-allocation algorithms from [14] have been used in this evaluation study of exploration strategies. The algorithms assign one or several goal candidates to each robot while only one goal candidate is considered as the goal towards which the robot is navigated. All the assigned goals to the robots form a disjoint set; thus, each goal candidate can be assigned only to one robot.

Greedy Assignment (GA) – A modified greedy assignment is utilized rather than the original approach proposed by Yamauchi in [17]. The closest not yet assigned goal is assigned to each robot sequentially; however, the assignment is performed for a random order of the robots to avoid preference of the first robots like in the original Yamauchi's approach.

Iterative Assignment (IA) – is based on the *Broadcast of Local Eligibility* [18], which is implemented in a centralized environment. The assignment is an iterative procedure, where all robot–goal pairs $\langle r, g\rangle$ are ordered by the associated distance cost. Then, the first not assigned goal from the sequence is assigned to the particular robot without an assigned goal.

Hungarian Assignment (HA) – The Hungarian method represent an optimal task-allocation algorithm for the given cost matrix in which each cell value is a distance cost of the robot–goal assignment. The algorithm has complexity $O(n^3)$, where n is the size of the squared cost matrix. If the number of goals is less than the number of the robots, the IA algorithm is used, while for a higher number of goals than the number of the robots, the cost matrix is enlarged and virtual robots are added with a very high cost for the goals. The used implementation of the Hungarian algorithm is [19].

Multiple Traveling Salesman Assignment (MA) – is motivated by the TSP distance cost [12], where the next robot goal is selected as the first goal on the route found as a solution of the Traveling Salesman Problem (TSP). Here, the distance cost is utilized in the extension of the multiple traveling salesman problem (MTSP) that is addressed by the ⟨*cluster first, route second*⟩ heuristic [13]. First, the goal candidates are clustered by the K-means algorithm where the clusters are seeded with the robots positions. Then, each cluster is assigned to the particular robot used for the cluster initialization and the next robot goal is determined according to the TSP distance cost. The solution of the TSP can be computationally demanding, and therefore, we consider Chained Lin-Kernighan heuristic [20] from the CONCORDE [21].

3.2. Goal Candidates Determination

In this study of exploration strategies and their parameters, we primarily consider the goal candidates that are determined by the method originally proposed for the TSP distance cost [12] to reduce the number of candidates and to allow a solution of the related TSP, because using all frontiers cells as the goal candidates can be quickly computationally intractable. The idea of this method is to use only several representatives of the frontiers cells from which all frontier cells can be covered by the robot's sensor from the representative. We follow the concept of free edges described in [8] and consider frontier cells in connected components. For simplicity we assume the freespace cells in $\mathcal{M}$ always form a single connected component (e.g., it is satisfied in a case when all robots start from the same location) and only frontier cells that are reachable by all robots are considered. All frontier cells $\boldsymbol{F}$ are organized into a set of o sets (called free edges) of the single connected components $\mathcal{F} = \{\boldsymbol{F}_1, \ldots, \boldsymbol{F}_o\}$ such that $\boldsymbol{F} = \bigcup_{i=1}^{o} \boldsymbol{F}_i$ and $\boldsymbol{F}_i \cap \boldsymbol{F}_j = \emptyset$ for $i \neq j$, $1 \leq i, j \leq o$. Similarly to [8], we consider only free edges that consist of more than n_f cells. In particular, $n_f = 2$ is used for the results presented in this paper.

Having a set of free edges $\mathcal{F}$, representatives of the free edges (RFE) are determined by the clustering algorithm as follows. For each free edge $\boldsymbol{F}_i$, K-means algorithm is used to find n_r clusters and the mean of each cluster is one goal candidate. The number n_r is determined according to the sensor range ρ_g (in the number of grid cells) as

$$n_r = 1 + \left\lfloor \frac{|\boldsymbol{F}_i|}{1.8\rho_g} + 0.5 \right\rfloor. \qquad (1)$$

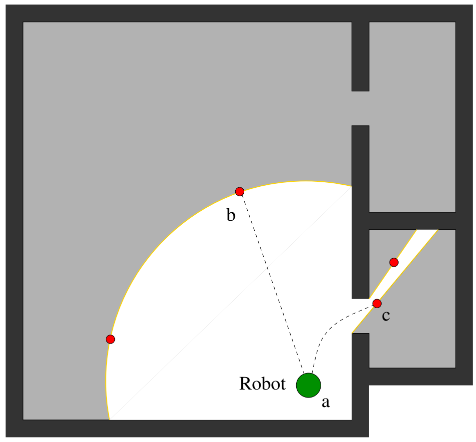
4. Discussion of Assumption and Approximations

4.1. Distance Cost vs. Time to Travel cost

The objective function of the studied exploration of unknown environment is the time to create a map of the environment. In the context of the selection of the robot goal, the problem can be defined as a problem to determine the next robot goal such that the assignment will minimize the total required time to explore the environment. However, the goals are usually assigned using a distance between the robot actual position and the goal candidate that is computed as a length of the shortest path from the robot to the goal. This is a common approximation as it is assumed the real traveled time is proportional to the path length, and we consider the robot is moving with some average speed. Besides, a more realistic estimation of the travel is usually computationally demanding as it needs to evaluate the used robot motion control.

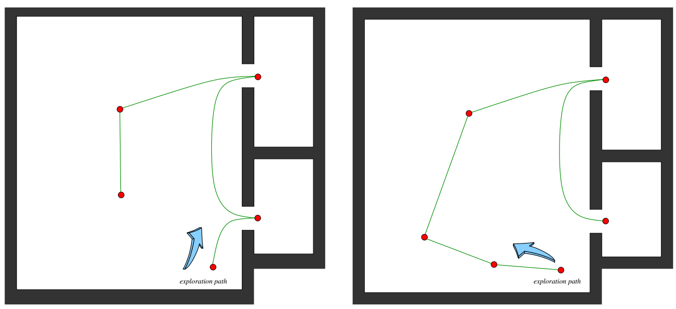
However, what will be the exploration performance if we have a more precise or even exact estimation of the time to travel to the goal. Does it make sense to improve local decision making by a more sophisticated estimation of the cost function? To answer this question, let consider the following thought experiment with one of the commonly used local planner called smooth nearness-diagram (SND) [22]. The SND utilizes a local map of the robot surroundings and it is able to safely navigate the robot through narrow corridors, where the velocity of the robot is decreased in a proximity to obstacles.

Imagine a situation visualized in Fig. 1, where the robot explores an area close to a room. There are two goal candidates denoted b and c. If we consider a greedy assignment with the distance cost, the goal candidate c is selected because it is closer to the robot. Then, the robot will likely explore the



(a)

Fig. 1. Local decision-making; light gray – unknown environment; dark gray – a real map of the environment; white – explored free space; yellow – frontiers (free edges); red discs – goal candidates (representatives of frontiers)



(a) preference of room exploration (b) preference of open space

Fig. 2. Examples of exploration paths with different paths lengths and exploration time; the left path is shorter but it may take a more time to pass the doors while the right path is longer but it can be faster due to maneuvering in narrow doors only three times

whole room and then it will continue with the exploration, but it will not need to return to visit c, e.g., the exploration path can as the one depicted in Fig. 2a.

On the other hand, if we consider the time to visit the goal candidates, the candidate b will be likely selected because the robot will reach it much faster than moving through door towards c. However, in the end, the robot needs to return to c as it needs to explore the room. Such a return trip can be significantly longer and more time consuming than the immediate visitation of the goal candidate c, e.g., as it is shown in Fig. 2b.

There is not a simple answer to the question which strategy is better and which one provides faster exploration of the whole environment. In practice (and for office like structured environment), it will likely be the first approach. This can be quite surprising as we consider a less precise approximation of the real time needed to travel to the goal. But it is simply because we cannot take into account the cost of the robot return, because we do not have enough information yet.

If we consider the TSP distance cost, which consider a longer planning horizon to visit all the current goal candidates, instead of the simple greedy assignment, the results will be similar. Notice, we are finding an open route starting from the robot position and ending at one of the goal candidates. Therefore, the first goal will be b because to visit c as the first goal the robot needs to pass the doors two times, which is a more time consuming than the travel to b and then to c.

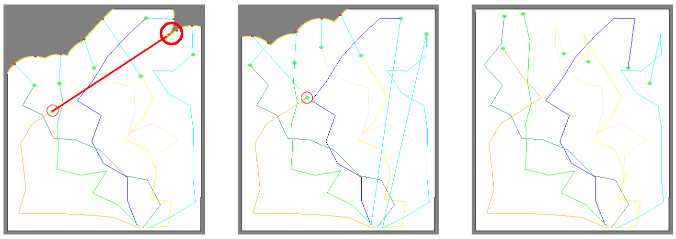
It is clear that a particular suitability of the goals selection depends on the ratio of the robot velocities in freespace and in a cluttered environment. However, the main point is that the locally more informed and precise estimation does not necessary mean a better overall performance. The assumption about the average robot velocity capture a longer planning horizon, and therefore, it actually provides a more suitable estimation, which is also supported by real experiments where greedy approaches works quite well and more informed approaches do not demonstrate the expected benefits. These observations are the reasons, why we consider distance between the robot and goal candidates in the assignment strategies, but consider discrete time to complete the exploration as the objective function in this study.

4.1.1. Task-allocation with return to the depot: To demonstrate an effect of local decision making with a consideration of a different planning horizon, we study situations where it is required the robots have to return to the starting position. Hence, regardless the order in which the robot visit the goals b and c in Fig. 1, it needs to pass the doors two times. Based on this observation, we propose the following modifications of the HA and MA assignments.

In the modified HA (denoted as HAd), the cost of the goal assignment g to the robot r is computed as a sum of the robot–goal path length, goal–depot path length, and the currently traveled path of the robot r:

$$c(r, g) = d(r, g) + d(g, depot) + \text{traveled\_distance}(r). \quad (2)$$

In the modified MTSP based assignment (denoted as MAd), the robot has to visit all the current goal candidates in the assigned cluster and from the last goal in the route, the robot has to move to the depot, which makes the tour length longer. Both these strategies are evaluated in a series of the trials to study if such extensions of the local task-allocation algorithms provide better overall exploration performance. A summary of the results is presented in Section 5.1.



(a) planning step 11 (b) planning step 12 (c) planning step 14

Fig. 3. An example of the situation, when a robot (in a red circle) has assigned goal, which will be more like covered by other robots because the goal is too far for the robot.

4.2. *Too Far Goal Candidates*

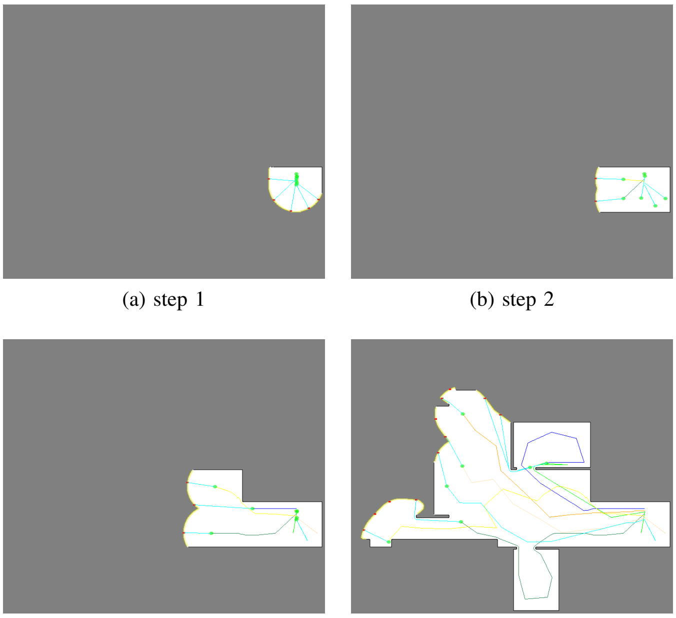
Another hidden pitfall of the task-allocation is shown in Fig. 3. There is a situation where a robot r finishes exploration of its part while most of the current frontiers are relatively far from it. However, there are still more goal candidates than the number of robots, and therefore, a goal relatively far from the robot r is assigned to it. But, because there are closer robots, the particular goal area will be covered by other robots and the robot will not reach the goal. Then, the same situation is repeated for the left located frontiers. What does it mean from the objective function point of view? If we consider the total exploration time, it does not matter the robot unnecessary moves even though it is probably a waste of its energy. On the other hand, if we approximate the exploration time as the length of the longest path traveled by a robot, these situations can make the performance unnecessary worse.

These examples demonstrate that a task-allocation based only on a simple distance cost does not provide the expected behavior. Moreover, it also demonstrate that we should probably need to consider the allocation in a longer planning horizon and visitation of the all current goal candidates in future planning steps. This is partially considered in the TSP distance cost, but it is not explicit. Therefore, we believe this insight provides a ground for a further development of a more complex assignment approaches that will improve the performance of the exploration.

4.3. *Too Few Goal Candidates*

Now imagine an exploration mission, where a relatively high number of robots is deployed and the robots are requested to return to the depot at the end of the exploration. In this scenario, the return might play a significant portion of the total traveled distance, especially in similar situations as in the aforementioned case with too far goals. Based on this observation, we can add a rule to the exploration strategy that a robot without an assigned goal will initiate return to the depot.

Although such a rule might save some distances to travel at the very end of the exploration mission, its influence to the



(a) step 1 (b) step 2

(c) step 35 (d) step 63

Fig. 4. An example of the situation, when couple of robots return to the depot and wait for additional new goal candidates appear.

performance is also related to the way how goal candidates are determined. The RFE method described in Section 3.2 determine the goal candidates independently to the number of robots in the team. Thus, it may happened that few goal candidates can be determined at the beginning of the mission, e.g., because the robots are placed in a long corridor. Such a situation with 7 robots is demonstrated in Fig. 4.

In the first steps, only two or three goal candidates are determined, which are assigned to the particular number of robots and the rest of the team stay at the depot. After several steps, larger areas of the environment are explored and the remaining robots travel to them and join the exploration process. This observation motivates us to modify the RFE method and adaptively increase n_r. Thus, if there is at least one free edge F_i, the expected total number of goal candidates is determined and if it is lower than the number of robots m, the particular n_r of the largest free edges are increased to have m goal candidates. This adaptive number of representatives method is denoted as the ANR in the rest of this paper and results of its influence to the exploration mission is presented in Section 5.3.

5. Results

The discussed variants of the exploration strategies based on the task-allocation problem formulation have been studied in four environments: *em*, *autolab*, *jh*, and *potholes*; with dimensions 21 m×24 m, 30 m×30 m, and 21 m×24 m, and 40 m × 40 m, respectively. The *em* is an environment without obstacles and three other environments are visualized in Fig. 5.

The evaluation study is considered for a different number of robots m selected from the set $m \in \{3, 5, 7\}$, sensor range ρ from the set $\rho \in \{3\text{ m}, 5\text{ m}, 7\text{ m}\}$. To evaluate sensitivity of the studied strategies to the starting positions of the robots, small random perturbation in the initial positioning are considered that gives 20 different initial conditions of the robot and particular problem. The starting locations of the robot in the particular environments can be seen in Fig. 3 and Fig. 5. Robots are disc shaped platforms with a diameter 0.3 m and paths are determined in an enlarged map to avoid collisions with obstacles.

Four basic task-allocation algorithms described in Section 3.1 (GA, IA, HA, and MA) have been employed accompanying by two modifications for the depot return scenario (HAd and MAd) introduced in Section 4.1.1. Two goal candidates determination methods have been combined with the task allocation algorithms, the RFE method (Section 3.2) and its adaptive modification ANR introduced in Section 4.3.

The GA, MA and MAd strategies are stochastic, and therefore, 20 trials are performed for each problem and particular initial locations of the robots. In addition, we consider two scenarios with and without the requirement the robots have to return to the depot that are denoted as OP (open paths) and RD (return depot). Besides, we consider two variants of the replanning: 1) goal replanning (GR); 2) and immediate replanning (IR) described in Section 2. Thus, the total number of the performed simulation trials is 362 880 and particular strategies are statistically compared using five points summary of the measured random variables for the required number of the exploration steps and the maximal traveled distance to explored the whole environment (and return to the depot for the RD missions).

Due to excessive number of the evaluated combinations and variants, we summarize the results and present only selected comparisons to support found insights.

5.1. Return to the Depot Strategies

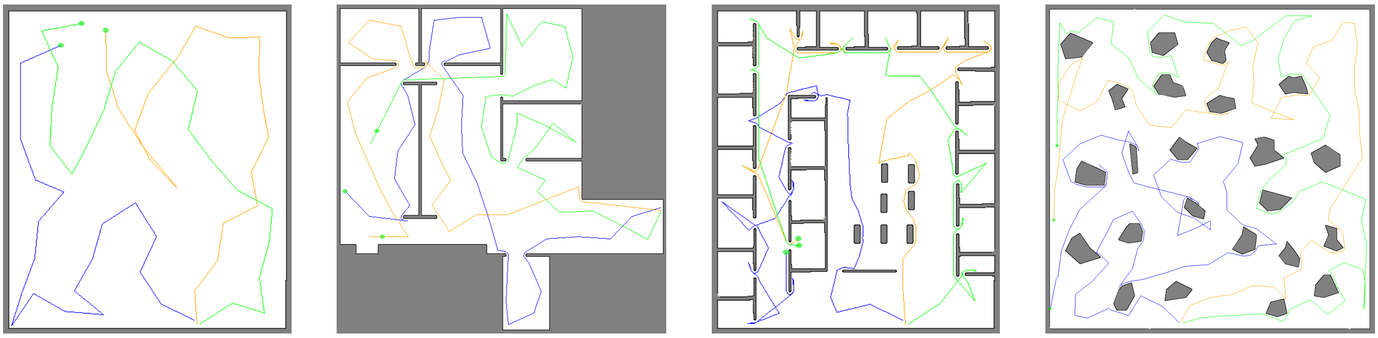
The modified task-allocation algorithms HAd and MAd (introduced in Section 4.1.1) do not provide expected improvements in the missions with the return to the depot at the end of the exploration. In most of the cases, the performance of these exploration strategies are worse than for the original HA and MA algorithms. However, two interesting cases can be observed for the *jh* environment, see Fig. 6, where it is visible how the requirement to return to the depot (RD) leads to a longer exploration paths.

In *jh* environment, the MAd strategy provides a better performance than the MA strategy in some cases for ρ=7 m. But for ρ=3 m, Hungarian task-allocation based strategies perform better than usage of the TSP distance cost.

These results indicate that the performance of the strategy is influenced by the structure of environment, where a longer sensing radius allows to explore whole rooms from the room entrance and thus considering expected length of the return path plays a more important role. Notice that in the showed results, the replanning is performed once a robot reaches its goal (GR). It can lead to a situation where for a small ρ the replanning is a more frequent than for a higher ρ, which also affect the mission performance.

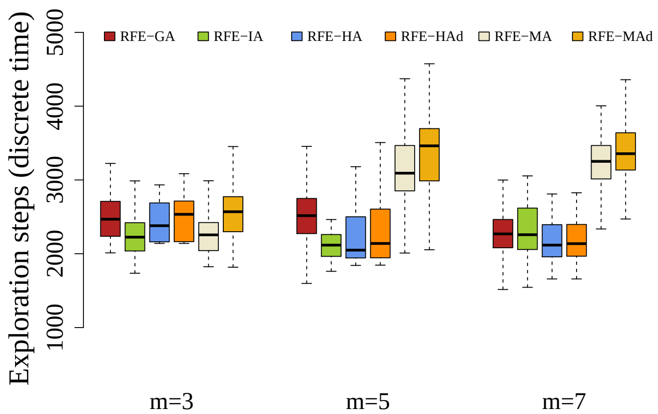
5.2. Influence of the Replanning Period

It is clear that one can expect a better performance for a faster replanning as a new decision is made based on new ac-

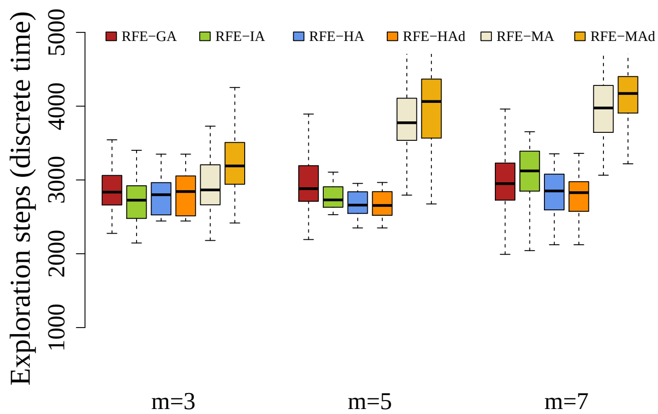


(a) *em* (b) *autolab* (c) *jh* (d) *potholes*

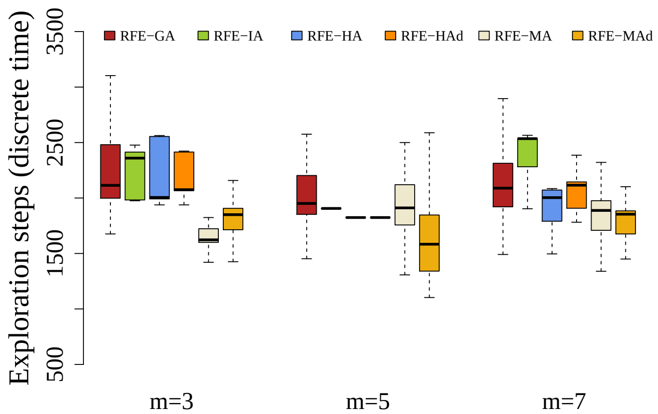
Fig. 5. Examples of exploration paths in the selected environments, the number of robots m=3, sensor range ρ=3 m and RFE-HA exploration strategy



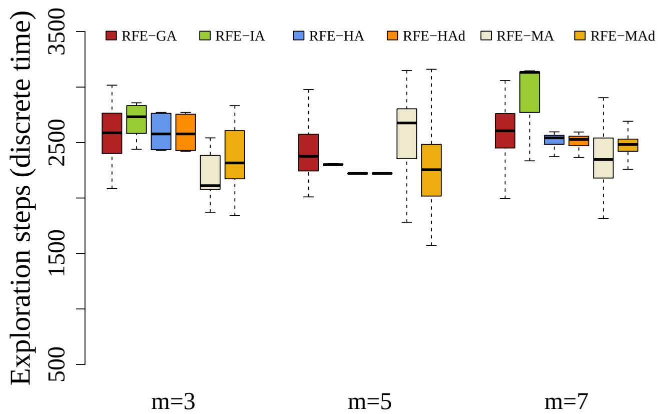
(a) *jh*, **OP**–GR, RFE, ρ=3 m



(b) *jh*, **RD**–GR, RFE, ρ=3 m



(c) *jh*, **OP**–GR, RFE, ρ=7 m



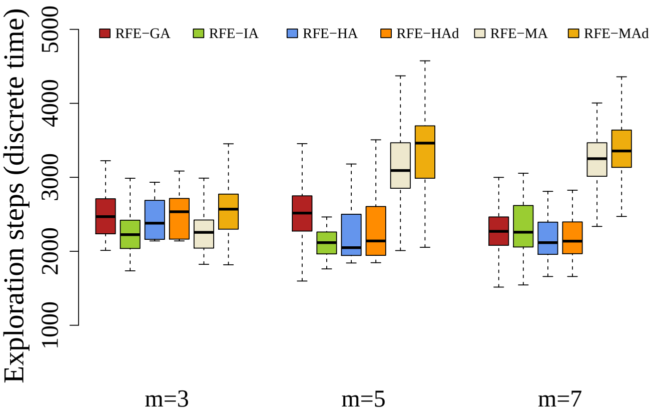
(d) *jh*, **RD**–GR, RFE, ρ=7 m

Fig. 6. Comparison of the exploration performance for open paths (OP) and return depot (RD) strategies using the longest traveled path, m robots, goal replanning (GR), and the RFE goal determination strategies

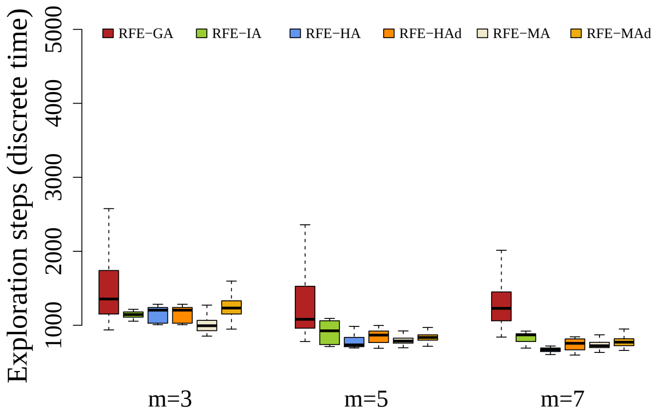
quired information about the environment being explored. We consider the goal replanning (GR) and immediate replanning (IR) (viz Section 2) to evaluate influence of the replanning period. The IR is the fastest replanning possible and thus it is also computationally very demanding. This is not an issue with the used discrete simulator, which allows evaluation of the exploration performance independently on the computational requirements and motion capabilities of robots.

Faster replanning improve performance of all strategies and selected comparisons are presented in Fig. 7 and Fig. 8. The reason for a very high standard deviations in greedy assignment (GA) for *jh* environment and IR (see Fig. 7b) is that in the combination with a lower number of the goal candidates than the number of robots determined by the RFE, the robots oscillate between the goals, which unnecessarily increases the traveled path. This is not the case for the GR, where at least one robot reaches its goal, and therefore, the robots usually do not oscillate between the goals.

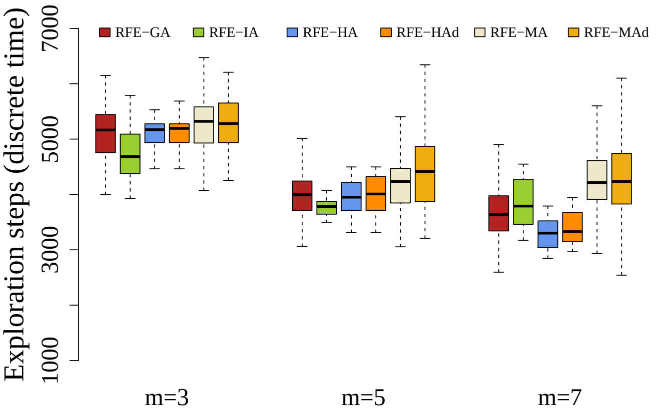
Determination of at least m goal candidates improves performance of the GA strategies with immediate replanning, see Fig. 8. A further study of this goal candidates determination method is presented in the next section.



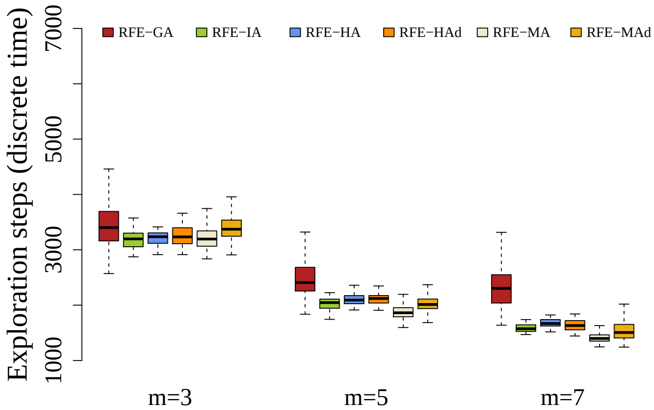
(a) *jh*, OP–**GR**, RFE, ρ=3 m



(b) *jh*, OP–**IR**, RFE, ρ=3 m

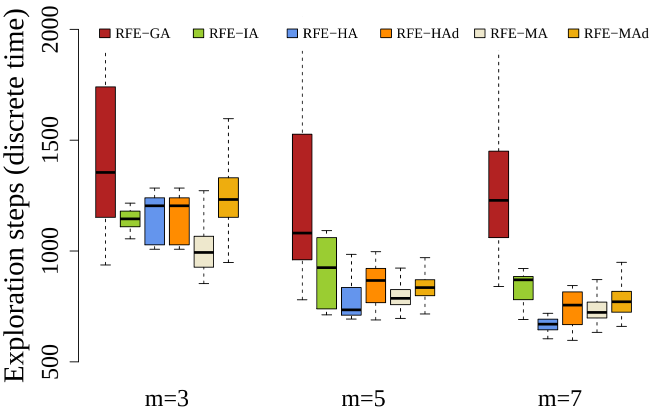


(c) *potholes*, OP–**GR**, RFE, ρ=3 m

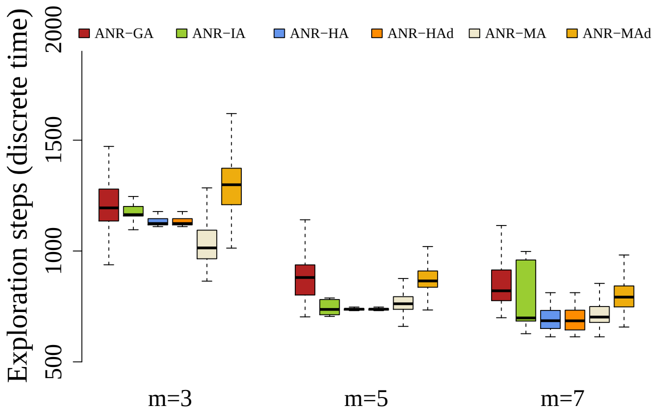


(d) *potholes*, OP–**IR**, RFE, ρ=3 m

Fig. 7. Comparison of the exploration performance for goal replanning (GR) and immediate replanning (IR) strategies with open paths (OP), m robots, ρ sensing range and the RFE goal determination strategies



(a) *jh*, OP–IR, **RFE**, ρ=3 m



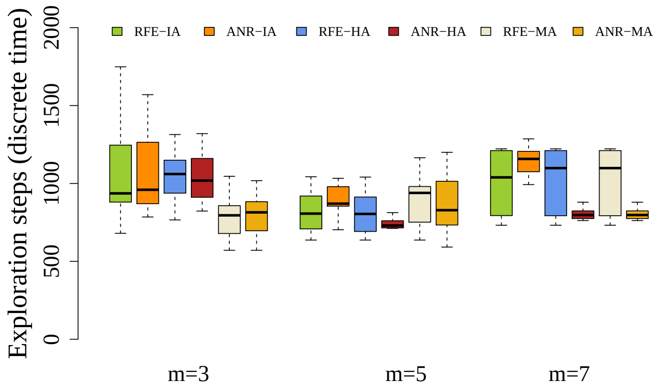
(b) *jh*, OP–IR, **ANR**, ρ=3 m

Fig. 8. Comparison of the exploration performance for the RFE and ANR determination of the goal candidates, open paths (OP), and immediate replanning (IR) strategies

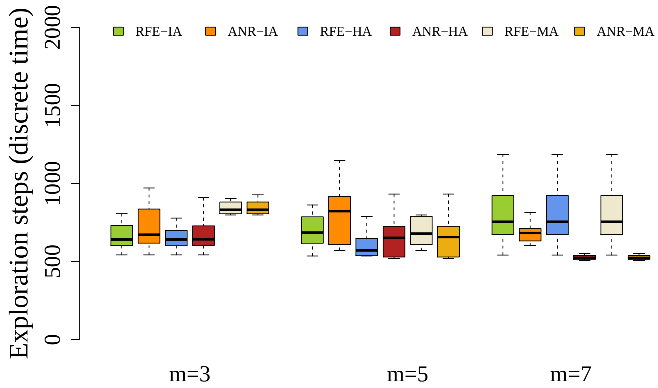
5.3. Adaptive Number of Representatives – ANR

The proposed ANR goal determination method that provides at least m goal candidates if there are uncovered reachable frontiers has been evaluated for all exploration strategies and their variants as the RFE goal determination. The ANR method is designed to address exploration missions with a high number of robots and low goal candidates at the beginning of the missions. On the other hand, it can also affect allocation of goal candidates to the robots at the very end of the missions. In most of the evaluated scenarios, the performance of the exploration strategies is better for ANR or both methods provides similar results; however, ANR leads to a more stable solution quality as the standard deviations are significantly lower than for the RFE. Selected results are depicted in Fig. 9, Fig. 10, Fig. 11, and Fig. 12.

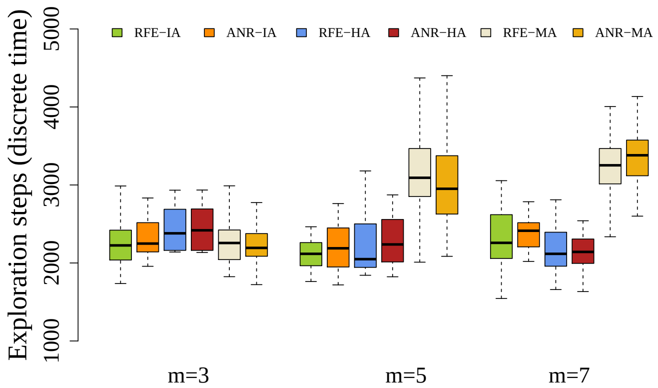
The main sources of the improvements provided by the ANR goal determination method is the fact that frontier



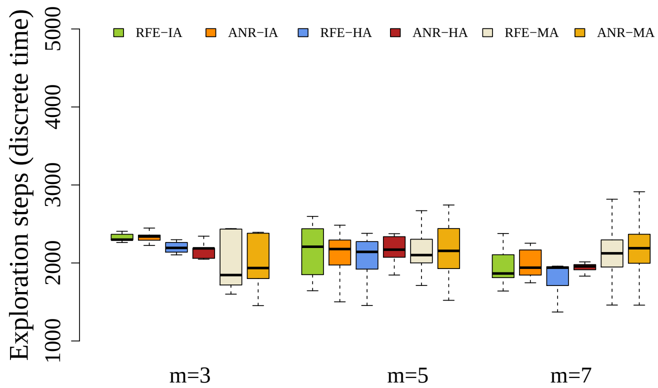
(a) *em*, OP–GR, ρ=5 m



(b) *em*, OP–GR, ρ=7 m

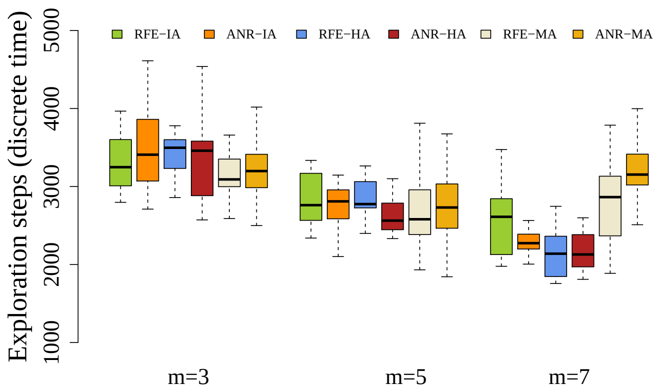


(c) *jh*, OP–GR, ρ=3 m

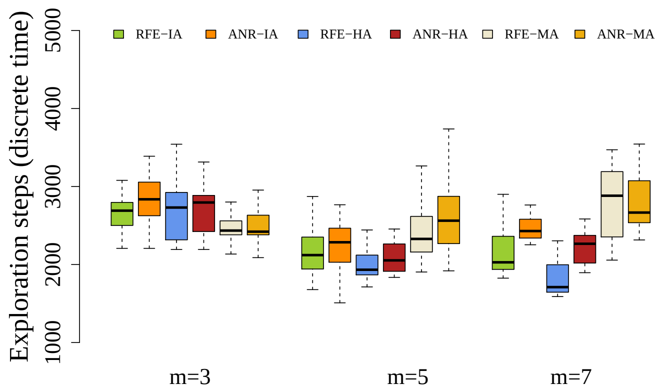


(d) *jh*, OP–GR, ρ=5 m

Fig. 9. Average maximal length of the exploration paths for a team of m robots, RFE and ANR goal determination methods, and goal replanning (GR) strategies with open paths (OP) and sensing range ρ



(a) *potholes*, OP–GR, ρ=5 m



(b) *potholes*, OP–GR, ρ=7 m

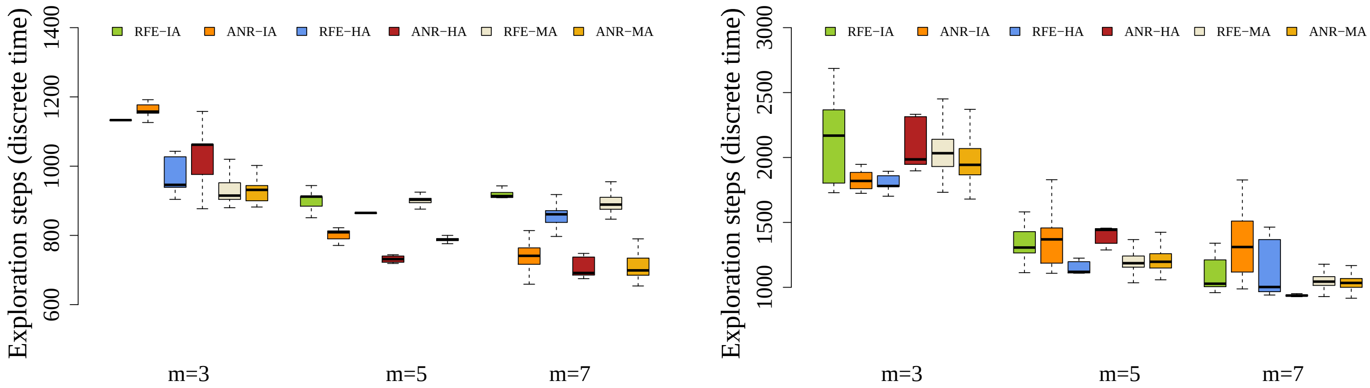
Fig. 10. Average maximal length of the exploration paths for a team of m robots, RFE and ANR goal determination methods, and goal replanning (GR) strategies with open paths (OP) and sensing range ρ

representatives can vary between replanning steps even for small changes in the current map of the environment. Adding more goal candidates improve division of the work among the team members during the initial and also final phases of the exploration, where there are only few free edges.

5.4. Discussion

The performed evaluation and selected results presented in this section provide a ground for the following insights:

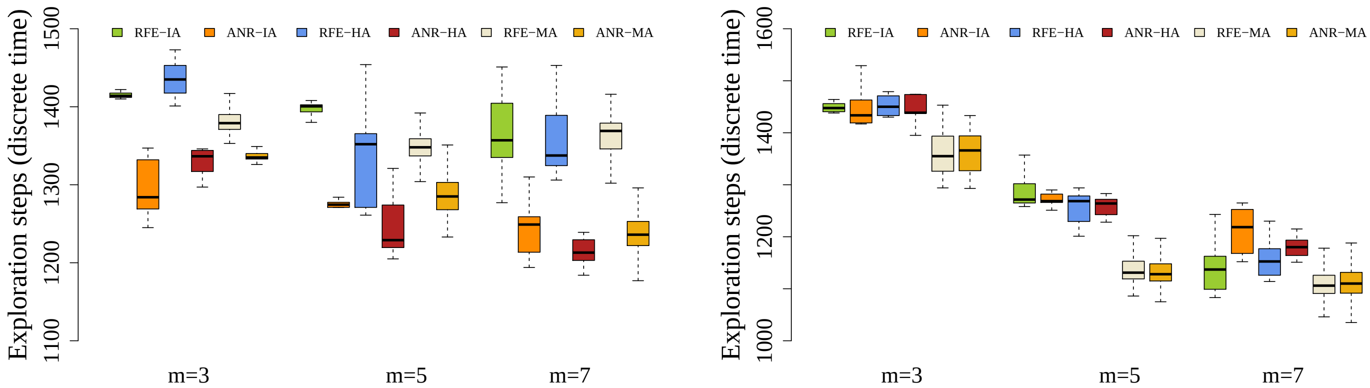
- The requirement the robots return to the depot generally increases the exploration path (time). The presented results also indicate that more sophisticated local decision-making procedures with considering a further return to the depot does not provide overall expected benefits in average.
- Replanning period can significantly affect performance of exploration missions. Faster replanning provides better results, but in practice, it is highly related to the computational requirements and available computational resources. Therefore, a faster and simpler method can provide better results than more sophisticated and more demanding methods, e.g., HA vs MA task-allocation



(a) *autolab*, OP–IR, ρ=5 m

(b) *potholes*, OP–IR, ρ=5 m

Fig. 11. Average maximal length of the exploration paths for a team of m robots, RFE and ANR goal determination methods, and immediate replanning (IR) strategies with open paths (OP) and sensing range ρ



(a) *autolab*, RD–IR, ρ=7 m

(b) *jh*, RD–IR, ρ=5 m

Fig. 12. Average maximal length of the exploration paths for a team of m robots, RFE and ANR goal determination methods, and immediate replanning (IR) strategies with return to depot (RD) and sensing range ρ

algorithms. This is an important aspect that has to be considered in evaluation of exploration strategies using real hardware. Moreover, an immediate replanning can show if the exploration strategy provides a stable assignment, which is not directly visible for very slow or goal replanning (GR) strategy.

- Although the motivation of the computationally demanding TSP distance cost leads to a lower number of goal candidates, it seems to be more suitable to generate a high number of goal candidates for a large teams of exploring robots. Such an issue has not been observed for single robot exploration or using just several mobile robots, but it is necessary to be considered for large teams.

From a top perspective, we can consider exploration strategies as heuristics that aim to estimate a structure of the environment, because the mission performance mostly depends on it. If we have a prior map of the environment, the problem will become a variant of inspection planning and globally optimal exploration paths can be determined. Here, it is worth mentioning that the evaluated strategies do not explicitly consider expected utility of visiting goal candidates, e.g., expected area that can be covered from the frontier cells. This aspect is wired in the used goal candidates determination as more candidates are placed along longer free edges, which represent a larger portion of the unexplored areas. In [9], authors support coordination of the robots by an explicit assignment of the unexplored areas to particular robots; however, such a strategy requires assumption about the maximal dimensions of the area being explored. On the other, such an assumption is also restrictive, because the environment is not completely unknown. Hence a fundamental aspect of the exploration strategies, what kind of assumptions and constraints are considered is an important part of the evaluation and also design of the exploration strategies.

6. Conclusion

In this paper, we aim to point out how evaluation and comparison of the exploration strategies can be affected by the underlying parameters of the decision-making systems and how local decisions may or may not improve the overall mission performance. We also aim to provide support that a shorter replanning period can significantly improve the performance and thus a comparison of different exploration strategies in real exploration missions may be tricky with a limited computational resources. A result of such an evaluation is for the particular missions and cannot be generalized to all systems and environments

On the other hand, a discrete time simulator used in the presented study provides a well defined environment, which is not limited by particular computational resources and thus it may provide a more general expectation about the strategy performance. However, expected performance improvements may not be meet in real missions, simply because of other factors.

Regarding these insights, we therefore do not conclude the paper with a statement that one strategy is better than another one. We rather encourage researchers in the field of mobile robot exploration to consider both evaluation methodologies: a) a simulation verification of the stability and expected performance of the exploration strategy in a well defined and computational resources independent framework with a statistical evaluation of the results; and b) a more realistic simulation or real experimental validation of the selected the most promising approaches.

Acknowledgments

The presented work is supported by the Czech Science Foundation (GAČR) under research project No. 13-18316P.

Computational resources were provided by the MetaCentrum under the program LM2010005 and the CERIT-SC under the program Centre CERIT Scientific Cloud, part of the Operational Program Research and Development for Innovations, Reg. no. CZ.1.05/3.2.00/08.0144.

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