# On Determination of Goal Candidates in Frontier-Based Multi-Robot Exploration

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*Abstract*— **Frontier-based approach can be considered as a de facto standard method for a mobile robot exploration task. Many variants have been proposed; however, relatively little attention has been made to study the influence of goal candidates generation to the performance of the exploration. In regular approaches, frontiers are considered as eventual goals for the next-best-view selection using a utility function combining a distance cost and expected information gain. The aim of this paper is to show that using goal candidates that are independent of the distance cost can improve the performance of exploration strategies. The found insights are supported by a statistical evaluation of thousands of trials performed for various environments.**

## I. Introduction

The problem of building a map of an unknown environment by a single or a group of mobile robots is called robotic exploration and first approaches addressing this problem have been proposed in eighties. The main idea to address the problem is to determine the next goals towards which the robots are navigated to collect new information about the environment. The fundamental approach to generate goal candidates is the frontier-based approach [1]. A frontier is an area between unknown and already explored space; hence, it is a good candidate to be the next goal because the robot will likely explore the unknown space during navigation towards the goal. Frontiers can be easily determined in a grid-based map, and therefore, the frontier-based exploration is usually combined with the occupancy grid for a straightforward integration of new sensor measurements. Thus, the frontier-grid-based exploration is one of the most popular exploration approaches because of its simplicity.

During exploration, robots are navigating towards goals assigned in the next-best-view manner. The goals are iteratively selected from the actual goal candidates (e.g., frontier cells) according to the selected optimization criterion. Here, it is worth to mention that in the case of multi-robot exploration such a problem formulation can be considered as the *task-allocation* problem, where the expected information gain of the goal candidate can be combined with the distance cost in the utility function [2], [3].

Computational requirements of the exploration strategy can be expressed in terms of the computational complexity of the assignment procedure that principally depends on the number of goal candidates $n$ and the number of robots $m$. The number of frontier cells can be easily in hundreds (or even thousands) for a moderate environment with dimensions in tens of meters and an occupancy grid with the cell size of units (or tens) of centimeters. A high number of frontiers is not a significant computational issue for simple assignment procedures like greedy or iterative assignments [1], [4], [5], [6]; however, it can be computationally demanding for more complex approaches providing a shorter exploration time like the Hungarian algorithm [7] with $O(n^3)$ or the *multiple traveling salesman* approach [8].

Considering complex assignment procedures, it is preferable to determine the minimal set of the most promising goal candidates to decrease the computational burden of the assignment procedure. Moreover, it can be desirable to have a set of goal candidates with small overlap of their coverage to avoid necessity of candidates re-evaluation if a goal is assigned to a robot, e.g., like in [5], or to allow usage of the optimal Hungarian algorithm for solving the assignment problem.

To the best of our knowledge, the determination of promising goal candidates using the frontier cells has not been systematically studied. Therefore, in the presented study, we examine influence of the goal candidates determination to the performance of the multi-robot exploration where the exploration strategy is formulated as the task-allocation problem. In addition, we propose a simple procedure for determining goal candidates considering a coverage of the current frontiers that decreases the total required exploration time also for simple greedy and iterative goal assignment methods. Hence, the proposed idea can be considered as complementary to the other approaches combining additional criteria, e.g., respecting localization and communication constraints.

The paper is organized as follows. In Section II, related approaches are briefly described and their main differences to the proposed idea are discussed. Section III defines the problem and the evaluation methodology together with the description of the evaluated task assignment procedures and goal candidates determination methods. The proposed goal candidates selection is described in Section IV. A comparative study of the methods is presented in Section V, discussion in Section VI and concluding remarks in Section VII.

## II. Related Work

The most straightforward generation of the goal candidates is to use all frontiers cells as the candidates. A simple filtration can reduce the number of candidates, e.g., considering only frontiers that are not too close to obstacle regions to increase safety of navigation [9]. Then, the next robot goal can be selected according to the candidate utility.

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In [5], a utility of the frontier cell is estimated using visibility to frontier cells assigned to other robots. Considering all possible frontier cells in the assignment would lead to a combinatorial explosion, and therefore, the authors rather consider an iterative approach in which the current most suitable frontier is determined for each robot and after that the utilities of all remaining frontiers are recomputed. The iterative assignment is also used in [10], where the frontier cost is computed with respect to a particular robot using clustering of all possibly reachable unknown cells using the K-means algorithm. If a frontier does not belong to the robot's cluster the frontier–robot distance is computed as a sum of the Euclidean cluster's center–frontier distances. Otherwise, the cost is determined as the length of the robot–frontier path. In both cases, an additional penalization is considered to avoid assignment of the frontiers that are within a sensor range distance from the assigned frontiers. The penalization is determined after each assignment and the cost of the particular frontiers are updated.

From another perspective, finding a minimum set of the goal candidates can be formulated as a variant of the *art gallery problem*, in which we are looking for the best possible locations to cover unexplored areas that are represented by the frontiers. This idea has been presented in [3], where the authors utilize the sensor placement algorithm [11] as a randomized greedy set coverage technique to find the best view locations to cover the frontiers organized into a single connected components called free curves. The goal candidates are randomly placed within the sensor range from the free curves and each candidate $q$ is evaluated using a utility function $g(q) = A(q)exp(-\lambda L(q))$, where $\lambda$ is a positive constant, $L(q)$ is the length of the robot–candidate path, and $A(q)$ is the expected maximal area of the unknown part of the environment that can be explored from the candidate $q$. A similar approach is considered in [12], where distance and utility costs are combined in the same way with an additional exponential term to consider orientation of the sensor at the goal candidate location. The feasibility of the selection of the goal candidates to cover frontier cells in 3D exploration is shown in [13]. Instead of direct coverage of frontiers, authors consider the so called void cells (unknown cells that are inside of the convex hull of the point cloud representing the sensor measurements).

The proposed goal candidates generation method (described in Section IV) follows the idea of covering frontier cells and it is mostly similar to approaches [3], [12]. However, it considers only the current known parts of the environment, i.e., no explicit assumption about the unknown parts is assumed. Besides, the candidates are selected from possible locations from which frontiers can be covered independently to the distance cost and the current positions of the robots; hence, it does not require any weight parameters and thus it can be simply used with any task-allocation procedure.

In addition, the generation of candidates is a deterministic procedure, which is probably the most important difference to the approach [3]. Although the authors of [3] comment the eventual oscillations related to the parameter $\lambda$, we found out that the oscillations are mostly related to the frequency of re-planning. If new goals are determined once a robot reaches the current goal, the oscillations are not a significant issue. However, for a more frequent re-planning, the randomized placement causes that new goals can be placed at different directions which can cause frequent changes of robot's heading. This behaviour disqualifies the randomized approach for a frequent re-planning, which can generally provide a better performance as it avoids situations when the robots are navigated towards the goal from which only the already explored area can be covered.

## III. Problem Definition and Evaluation Methodology

In the presented study of the goal candidates generation, we consider the exploration as a repetitive solution of the task-allocation problem, where at each step, $n$ goals at the locations $\boldsymbol{G} = \{g_1, \ldots, g_n\}$ are allocated to $m$ robots at the locations $\boldsymbol{R} = \{r_1, \ldots, r_m\}$. At each such a decision step, the problem can be defined as follow. *Determine the next goal $g \in \boldsymbol{G}$ for each robot $r \in \boldsymbol{R}$ such that the assignment will minimize the total required time to explore the whole environment*. We assume an omnidirectional sensor consisting of two regular laser scanners with the range $\rho$, each with 180° field of view, providing 722 distance measurements in total with a high frequency (relatively to the speed of the robot), i.e., the sensing cost is negligible. The required exploration time is approximated by the maximal travelled distance by an individual robot. Having $m$ robots with the travelled distances $l_1, l_2, \ldots, l_m$ the performance metric is $L = \max\{l_1, l_2, \ldots, l_m\}$.

As we are interested in studying the mechanisms of the goal candidates determination, we consider the exploration in a simulator providing a precise definition of the particular exploration scenario and identical initial conditions for all studied strategies like in the studies [14], [15], [8]. In particular, we use the multi-robot exploration framework described in [8]. The framework allows a focused study of the decision mechanisms without influence of other parts of the real navigation system, which may affect the performance significantly. It also allows to evaluate the results statistically using thousands of simulations, which are unlikely possible with real robots. However, it is worth to mention that the found insights based on the proposed methodology represent foundations for further development and verification of the proposed techniques in real practical scenarios.

A brief overview of the exploration framework is presented in Section III-A and selected assignment strategies and goal determination methods are described in Section III-B and Section III-C, respectively.

### A. Multi-Robot Exploration Framework

The framework is basically an iterative procedure consisting of determination of the goal candidates, their assignment to the robots, and navigation of the robots towards the new goals. The detailed description can be found in [8], and therefore, only a summary of the procedure is presented here.

1) Initialize the occupancy grid $Occ$ and integrate the first sensor measurements.
2) Create navigation grid $\mathcal{M}$ from $Occ$, where each cell in $\mathcal{M}$ has value from $\{freespace, obstacle, unknown\}$.
3) Detect all frontiers, $\boldsymbol{F} = \text{detect\_frontiers}(\mathcal{M})$.
4) Determine goal candidates $\boldsymbol{G}$, $\boldsymbol{G} = \text{generate}(\boldsymbol{F})$.
5) Assign the next goal to each robot $r \in \boldsymbol{R}$, $(\langle r_1, g_{r_1}\rangle, \ldots, \langle r_m, g_{r_m}\rangle) = \text{assign}(\boldsymbol{R}, \boldsymbol{G}, \mathcal{M})$ .
6) Create a plan $\boldsymbol{P_i}$ for each pair $\langle r_i, g_{r_i}\rangle$, which is a sequence of simple operations (a movement of the robot about single cell or turn).
7) Perform the plans up to $s_{max}$ steps and at each step, update $Occ$ using new sensor measurements.
8) If $|\boldsymbol{G}| > 0$ go to Step 3, otherwise terminate.

The parameter $s_{max}$ precisely defines the re-planning period, which also affects the performance of the exploration [8]. A small $s_{max}$ provides a frequent re-planning while $s_{max}$=$-1$ is considered for re-planning after a robot reaches its goal. A localization based on scan alignment techniques is supported by a laser scanner with a high frequency sensing that provides overlapping scans, which is simulated by taking laser measurement at each grid cell.

### B. Goal Assignment Strategies

The effect of the goal candidates selection has been studied using four goal assignment strategies for the multi-robot exploration in which only the distance cost is considered. For the first three strategies, the distance cost is the length of the shortest robot–goal path, and for the fourth method the cost is the TSP distance cost [16]. In addition, we consider the approach [10] for a coordinated multi-robot exploration based on clustering of an unknown space. All goal–robot paths are found by the Distance Transform algorithm [17] with a simple smoothing [8].

**Greedy Assignment (GA)** – We use a modified greedy assignment approach [18] in which the best not assigned goal is assigned to each robot sequentially, while the robots are selected in a random order to avoid preference of one robot.

**Iterative Assignment (IA)** – The iterative assignment is a centralized implementation of the iterative procedure called *Broadcast of Local Eligibility* [4], where all robot–goal pairs $\langle r, g\rangle$ are ordered by the associated distance cost. Then, the first not assigned goal from the ordered sequence of pairs is assigned to the particular robot without an assigned goal.

**Hungarian Assignment (HA)** – The Hungarian method provides the optimal assignment using the cost matrix, where each cell represents the value of the distance cost for a robot–goal assignment $\langle r, g\rangle$. The C implementation [19] is used for the results presented in this paper.

**Multiple Traveling Salesman Assignment (MA)** – The assignment problem is formulated as the multiple traveling salesman problem (MTSP) that is solved approximately using $\langle$*cluster first, route second*$\rangle$ heuristic [8]. The clusters are found by the K-means algorithm and the next goal is selected from the particular cluster according to the TSP distance cost using the Chained Lin-Kernighan heuristic from the CONCORDE solver [20].

**Solanas and Garcia Assignment (SGA)** – This exploration strategy (proposed by Solanas and Garcia in [10]) represents a distance cost approach, where the coordination of the robots is supported by clustering unknown cells into $m$ clusters. After the first clustering (initialized by the map's center), the clusters are associated to the robots for the rest of the exploration. The next clustering is initialized by the previous clusters' centers. For the frontier $f_i$, robot $r_j$ and its cluster $\zeta_j$ the cost is

$$cost_{ij} = \begin{cases} \Delta + |f_i - \text{center}(\zeta_j)|_2 + o_{ij} & f_i \notin \zeta_j \\ \text{path\_length}(f_i, r_j) + o_{ij} & f_i \in \zeta_j \end{cases}, \quad (1)$$

where $\Delta$ is the length of the map diagonal, $o_{ij}$ is an additional penalization and $f_i$ is associated to the cluster with the closest center. A frontier $f^*$ with the minimal value of the cost (1) is selected for each robot and $2\rho$ penalization is added to $o_{ij}$ for each frontier that is within $\rho$ distance from $f^*$. In the original algorithm, a new goal is determined after a robot reaches its previous goal. However, based on the evaluation of the strategy performance we rather consider re-planning after $s_{max}$=7 steps, which provides up to 3 times shorter exploration paths, at the cost of a more aggressive robot control.

### C. Determination of Goal Candidates

The studied methods of goal candidates generation are based on determination of frontier cells in the navigation grid $\mathcal{M}$ as freespace cells incident with unknown cells considering 8-neighbourhood. We assume (without lost of generality) the freespace cells in $\mathcal{M}$ form a single connected component and consider only frontiers that are reachable by all robots. The set of all frontiers is denoted as $\boldsymbol{F}$.

The frontier cells are formed into connected components representing the free edges described in [3], [6], i.e., a set of all frontier cells $\boldsymbol{F}$ is organized into a set of $k$ sets (free edges) $\mathcal{F} = \{\boldsymbol{F}_1, \ldots, \boldsymbol{F}_k\}$ such that $\boldsymbol{F} = \bigcup_{i=1}^{k} \boldsymbol{F}_i$ and $\boldsymbol{F}_i \cap \boldsymbol{F}_j = \emptyset$ for $i \neq j$, $1 \leq i, j \leq k$. An example of the frontier cells organized into free edges is shown in Fig. 1a. Moreover, we follow the approach presented in [3] and consider only frontiers that are from free edges that have more than $n_f$ cells, i.e., $|\boldsymbol{F}_i| \geq n_f$ for $\boldsymbol{F}_i \in \mathcal{F}$.

1) **All frontiers (AF)** – The first selection method is a simple consideration of all frontiers. Although the framework allows to consider the AF method for the HA and MA exploration strategies, the required computational time is high, and for hundreds of frontiers such a combination of the methods is not suitable for real navigation.

2) **Representatives of Free Edges (RFE)** – This method is an accompanying goal candidates generation to the TSP distance cost introduced in [16]. The idea is to use only few goal candidates representing the free edges and from which all frontier cells would be covered (if a robot would visit the representatives). The representatives are means of $n_r$ clusters that are found for each free edge $\boldsymbol{F}_i$ using the K-means clustering algorithm. The number of representatives $n_r$ is determined considering the range of the sensor $\rho_g$ (in the number of grid cells) as $n_r = 1 + \left\lfloor \frac{|\boldsymbol{F}_i|}{1.8\rho_g} + 0.5 \right\rfloor$.

## IV. Goal Candidates Covering Frontiers

The proposed goal candidates generation algorithm follows the idea of representatives (RFE) and generation of samples covering free curves proposed in [3]. The problem is formulated as a variant of the art gallery problem with limited visibility, i.e., the problem stands in finding the minimal number of locations to cover all the frontiers $\boldsymbol{F}$ using an omnidirectional laser scanner with the range $\rho$. Contrary to [3], the proposed algorithm is an iterative deterministic procedure that is denoted as the **Complete Coverage (CC)** here. The procedure is summarized in Algorithm 1.

**Algorithm 1**: Goal Candidates Covering the Frontiers

**Input**: $(\boldsymbol{F}, \rho, \mathcal{M})$ - $\boldsymbol{F}$ a set of all reachable frontiers, $k = |\boldsymbol{F}|$, $\rho$ - the range of the sensor, $\mathcal{M}$ - the current navigation grid

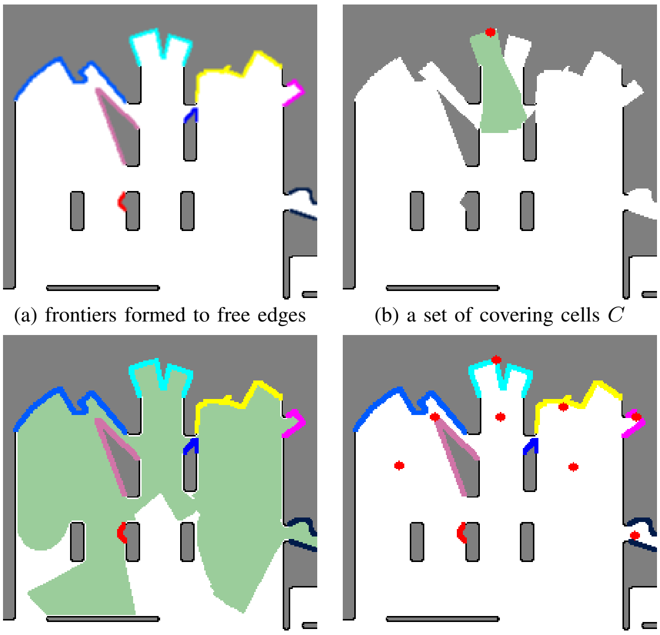
**Output**: $\boldsymbol{G}$ - a set of goal candidates

1 $\boldsymbol{G} = \emptyset$ // initialize the goal candidates
2 **foreach** $f_i \in \boldsymbol{F}$ **do**
3 $\quad C_i = \text{get\_covering\_cells}(f_i, 0.8\rho, \mathcal{M})$
4 $\boldsymbol{C} = \bigcup_{i=1}^{k} C_i$ // join the covering cells
5 $\mathcal{S} = \emptyset$ // set of covered cells for $c \in \boldsymbol{C}$
6 **foreach** $c_i \in \boldsymbol{C}$ **do**
7 $\quad S_i = \text{get\_covered\_frontier\_cells}(c_i, \boldsymbol{F})$
8 $\quad \mathcal{S} = \mathcal{S} \cup \langle c_i, S_i \rangle$ // associate $c_i$ with $S_i$
9 $\boldsymbol{U} = \boldsymbol{F}$ // initialize uncovered frontiers
10 **while** $|\boldsymbol{U}| > 0$ **do**
11 $\quad \langle c_i, S_i \rangle = \text{argmax}_{c_i \in \boldsymbol{C}, c_i \notin \boldsymbol{G}}(|S_i \setminus (\boldsymbol{F} \setminus \boldsymbol{U})|)$
12 $\quad \boldsymbol{U} = \boldsymbol{U} \setminus S_i$
13 $\quad \boldsymbol{G} = \boldsymbol{G} \cup \{c_i\}$

First, for each frontier cell $f_i$ a set of cells from which $f_i$ can be covered by the sensor with the $0.8\rho$ range is determined (Line 3) using a ray casting technique. A shorter range is used to support navigation towards frontiers. Then, the goal candidates are iteratively selected from the covering cells $\boldsymbol{C}$ until all the frontiers are covered. The covering cell $c_i$ with the maximal coverage of the not yet covered frontiers is selected in each iteration (Line 11). A visualization of determination steps is shown in Fig. 1. In this example, the original number of frontiers cells is 815 and the number of the final found goal candidates is 10, which represents a significant reduction allowing to consider the exploration strategy as the MTSP.

## V. Results

A ground for a discussion of the goal candidates determination methods is based on a statistical evaluation of exploration performance using the considered goal assignment and candidate generation methods. The results have been obtained using the multi-robot exploration framework and a set of problems within three representative environments called, *em*, *jh* and *potholes*. The *em* environment is an open space area without obstacles with the dimensions 21 m×24 m, which mainly serves to study how the strategies

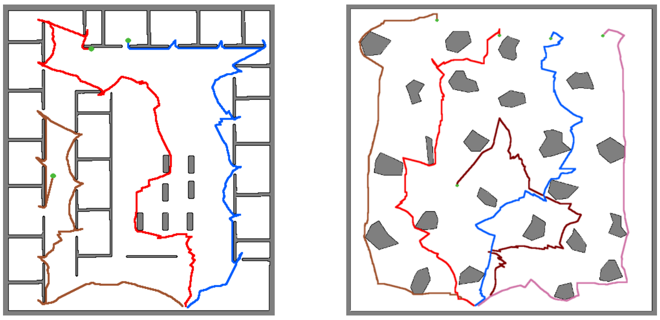


(a) frontiers formed to free edges (b) a set of covering cells $C$

(c) all covering cells $\boldsymbol{C}$ (d) all determined goal candidates

Fig. 1. An example of goal candidates covering the frontiers: (a) the current frontiers formed into single connected components representing the free edges, each component has different color; (b) a frontier showed as a red disc and all cells from which the frontier is covered (showed as green region); (c) all covering cells $\boldsymbol{C}$; (d) the final set of goal candidates showed as red discs. The free edges (frontiers) are enlarged for a better visualization.

can split the work to particular robots. The *jh* environment is a real administrative building with the same dimensions as the *em* and it contains several rooms. The *potholes* environment represents 40 m×40 m large open space with several obstacles. The environments are visualized in Fig. 2.



(a) *jh*, $\rho$=4 m, $m$=3 (b) *potholes*, $\rho$=5 m, $m$=5

Fig. 2. An example of the found solutions using the MTSP assignment and the proposed CC goal candidates generation.

The considered statistical evaluation methodology is based on [8] that follows recommendations for benchmarking exploration strategies [14]. Each problem is defined by the environment, number of robots $m$, sensor range $\rho$, and the goal assignment and goal candidates generation methods. For each problem, small perturbations in the initial robot positions are considered, which gives 20 variants of each problem. Moreover, for the stochastic assignment methods (GA and MA) 20 trials are performed for each particular problem variant. The number of robots is $m \in \{3, 5, 7, 10\}$ and the sensor range is $\rho \in \{3, 5, 7\}$ meters. In all trials, the minimal number of frontier cells in a free edge is $n_f$=1 and the planning period is set to $s_{max}$=7, which provides the best

TABLE I

COMPARISON OF THE EXPLORATION STRATEGIES IN *em/jh/potholes* ENVIRONMENTS

| $\rho$ | $m$ | **IA–CC vs IA–RFE** | **HA–CC vs HA–RFE** | **MA–CC vs MA–RFE** | **HA–CC vs MA–RFE** | **HA–CC vs MA–CC** | **IA–CC vs HA–RFE** | **IA–CC vs MA–RFE** | **IA–CC vs HA–CC** | **IA–CC vs SGA–AF** | **HA–CC vs SGA–AF** | **MA–CC vs SGA-AF** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3.0 | 3 | =/+/+ | +/+/= | +/+/+ | =/–/+ | =/–/= | =/+/+ | –/–/+ | –/=/= | =/+/+ | +/+/= | +/+/= |
| 3.0 | 5 | +/+/= | +/+/+ | =/=/+ | +/+/+ | +/+/= | +/=/+ | +/–/+ | =/–/= | +/=/= | +/+/+ | +/+/+ |
| 3.0 | 7 | +/+/= | +/+/– | =/+/+ | +/+/= | +/+/= | =/+/– | +/+/= | =/=/= | =/+/+ | =/+/+ | –/=/+ |
| 3.0 | 10 | =/+/+ | =/=/+ | =/+/+ | =/+/+ | =/+/+ | =/=/= | =/+/+ | =/=/= | =/+/+ | =/+/+ | =/+/= |
| 5.0 | 3 | +/=/+ | +/=/+ | +/+/+ | +/–/+ | =/–/= | +/=/+ | +/–/+ | +/=/= | +/=/+ | +/=/= | +/+/+ |
| 5.0 | 5 | =/=/+ | =/+/– | +/+/+ | +/–/+ | +/–/+ | =/=/– | +/–/+ | –/–/= | =/=/= | +/=/= | =/+/= |
| 5.0 | 7 | =/+/+ | =/+/+ | +/=/+ | =/+/+ | =/+/+ | =/+/+ | =/=/+ | =/–/= | =/+/+ | =/+/+ | =/+/+ |
| 5.0 | 10 | =/=/+ | =/+/+ | –/+/+ | =/+/+ | =/+/= | =/=/+ | =/=/+ | =/–/+ | =/+/+ | =/+/= | =/+/= |
| 7.0 | 3 | =/=/– | =/=/+ | +/=/+ | =/–/+ | =/–/= | =/=/– | =/–/– | =/=/= | –/–/– | =/–/= | –/+/+ |
| 7.0 | 5 | –/+/+ | –/+/+ | –/–/+ | –/–/+ | =/–/= | –/=/+ | –/–/+ | =/–/= | –/–/= | –/–/+ | –/+/+ |
| 7.0 | 7 | –/+/+ | –/+/+ | –/–/+ | –/+/+ | =/+/+ | –/+/+ | –/=/+ | =/–/– | –/+/+ | –/+/+ | –/+/+ |
| 7.0 | 10 | –/+/+ | –/=/+ | –/=/+ | –/+/+ | =/+/= | –/=/+ | –/+/+ | =/=/= | =/+/+ | =/+/+ | =/+/+ |

performance for all methods. The methods are combined as follows. The assignment methods GA, IA, and HA have been combined with the AF, RFE, and CC generation schemata. The MTSP Assignment (MA) is considered with the RFE and CC schemata. The coordinated approach [10] (called SGA here) is considered only as the SGA–AF. The total number of the evaluated trials is about two hundred thousands but due to the limited space only selected results are presented.

The evaluation is based on testing a null hypothesis that the strategies provide statistically identical results for the performance indicator $L$ considered as a random variable over all perturbations and particular trials. The distributions of the performance metrics are not Gaussian (based on the Shapiro-Wilk test), and therefore, we evaluate the hypothesis using the Wilcoxon test. The strategies are considered different if difference between distributions of $L$ is statistically significant, i.e., P-value of the Wilcoxon test is smaller than 0.001. The statistical comparison of the strategies is shown in Table I, where characters '-', '+' and '=' denote the particular strategy provides longer, shorter, or statistically identical $L$. The characters are determined according to P-values and in the case of statistically different distributions, the strategy providing a smaller average value of $L$ is considered as a better. So, *"a vs b:* **+***"* means the strategy $a$ is better than $b$.

In addition, indicative results of the MTSP assignment using all frontiers (MA–AF) are depicted in Table II to show computational requirements. The results have been obtained using 2.8 GHz CPU and C++ implementation, the required computational time $T_{cpu}$ is in seconds. Using all frontiers in the MA is not computationally feasible for a real navigation. The CC goal generation is a more computationally demanding than RFE, but still computationally feasible.

TABLE II

INDICATIVE RESULTS FOR THE TSP DISTANCE COST ASSIGNMENT

| $\rho$ | **MA–AF** | | **MA–RFE** | | **MA–CC** | |
|---|---|---|---|---|---|---|
| | $L$ | $T_{cpu}$ | $L$ | $T_{cpu}$ | $L$ | $T_{cpu}$ |
| 3.0 | 173.0 | 63 050 | 168.8 | 141 | 160.8 | 403 |
| 4.0 | 149.8 | 60 834 | 152.9 | 171 | 147.6 | 557 |
| 5.0 | 139.6 | 74 479 | 137.2 | 237 | 137.4 | 883 |

## VI. DISCUSSION

The statistical comparison provides a ground for a discussion about an impact of the goal candidates determination methods to the performance of the exploration strategies. In a multi-robot exploration, it makes no sense to consider all frontiers in the greedy assignment, because robots can be navigated towards goals with a similar goal distance; hence, towards the same area. The SGA–AF method (similarly to [5]) addresses this issue by the penalization of the frontiers that are within the sensor range from the already assigned goals. The presented results indicate that this issue can also be addressed by selecting goal candidates, which naturally support distributions of the robots among the environment.

The CC method improves performance of all evaluated goal assignment strategies. RFE has been combined with the GA, HA, and MA approaches in [8], where the MA provides the superior results. However, using the proposed CC method, differences between the assignment methods are smaller. The HA–CC method provides (in most cases) better results than the MA-RFE approach; thus, the relatively simple HA method provides competitive solutions to a more complex MTSP assignment. Regarding the SGA–AF strategy, other strategies provide mostly statistically identical or better results than the SGA–AF. All the approaches use only the distance cost; however, the SGA–AF approach introduces additional penalization and it re-evaluates the goal costs after each assignment. The GA assignment provides the worse performance (not included in Table I due to space constraints) but CC improves its performance over the RFE.

Based on the results, the IA–CC provides competitive results to other strategies. The main advantage of the IA is a straightforward implementation in a decentralized environment, and therefore, the IA–CC is a suitable approach for a distributed decision making in the multi-robot exploration.

### A. Notes about Deployment of the Exploration Strategies

The considered evaluation framework provides a focused test bed, where the fundamental properties of exploration strategies can be studied and which can be hidden when the strategies are evaluated in a practical deployment, where the real performance depends on many other factors. This is visible for a frequent re-planning, which generally can improve the performance, e.g., see [8]. However, if positions of the goal candidates are significantly changed between re-planning steps, the robots can oscillate between the goals and the whole performance is decreased like for the approach [3]. Such a behavior may not necessarily be observable for a less frequent re-planning limited by available computational power; hence, the used framework is beneficial.

Regarding the re-planning frequency, the studied strategies provide statistically equivalent performance for re-planning after a robot reaches its goal (results not presented here). A more frequent re-planning improves the performance of all of them and makes differences between the strategies statistically noticeable. From this observation, it is obvious the performance of the methods may be different in a practical deployment. Thus, an initial evaluation has been performed in a more realistic setup using the Player/Stage framework and the SND navigation [21]. The robots are continuously navigated towards their actual goals, while the re-planning is performed as frequently as possible.

The preliminary evaluation provides statistically equivalent results for the RFE and CC methods. It is because the CC method is a more demanding than RFE, which can be even more significant for a larger set $\boldsymbol{C}$ considering a restricted field of view, where each goal candidate includes also the desired orientation of the robot like in [12].

In this deployment, we also have found out that the real required time to explore the environment is mostly affected by the SND navigation, which slows down the robot in the vicinity of obstacles, e.g., in doors. Hence, the exploration time mostly depends on the number of rooms while long travels in an open space are fast and do not affect the exploration time significantly. Therefore, the expected travel time seems to be a more suitable metric than the pure distance cost, which deserves a further investigation.

## VII. Conclusion

In this paper, we discuss a problem of determining goal candidates in the multi-robot exploration. The study is motivated by our previous work on the TSP distance cost in which a smaller number of candidates is a more desirable than considering all frontier cells because of the computational burden. The presented results indicate that generating goal candidates can make a less complex task-allocation approaches (i.e., the iterative and Hungarian methods) competitive to the complex MTSP based assignment. Moreover, they provide expectations of better results than approaches based on a penalization of frontiers and re-evaluation of the cost function, which are not suitable for distributed environment because of needed communication. Thus, the results support the idea of a simple goal assignment accompanied by a determination of promising goal candidates.

Regarding a practical deployment of exploration strategies, we found out the performance significantly depends on the real travel time to the goal rather than on the exploration strategy itself. Besides, the current implementation of the CC method is computationally demanding, which decreases the achievable re-planning frequency using on-board resources. We also found out that a frequent re-planning needs "stable" locations of the goal candidates to avoid changes of the robots' heading. These issues are subjects of our future work.

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