# Decentralized Task Allocation in Multi-robot Exploration with Position Sharing Only

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**Abstract.** This paper is concerned with multi-robot exploration in environments with limited communication that is supposed to be unreliable. The communication is low bandwidth, sufficient only for sharing positions of the robots, and does not allow sharing maps of the environment. Under these constraints, we propose to address the multi-robot exploration as a decentralized task allocation to coordinate robots in the exploration mission while exchanging only their positions. The feasibility of the proposed approach has been validated in various simulated scenarios within the virtual cave circuit environments of the DARPA Subterranean Challenge. The reported results indicate the proposed approach yields shorter or competitive average longest traveled paths than the decentralized MinPos method with the allowed sharing of full environment maps. The introduced method thus represents a suitable choice for decentralized task allocation in limited communication scenarios.

**Keywords:** task allocation, mobile robot exploration, low-bandwidth communication, MinPos

## 1 Introduction

Autonomous robotic exploration is an essential task for applications where humans are exposed to danger, such as search-and-rescue missions recently addressed within the DARPA Subterranean Challenge [1] to reach current technological limits in exploring abandoned mines, urban environments, and unknown caves. The natural way to increase autonomous exploration effectiveness is to employ multiple exploring units and address multi-robot exploration. However, the effectiveness of multi-robot exploration still depends on many factors, including sensory equipment, localization system, mapping and navigation algorithms, communication technology, and coordination strategy. Each of these factors represents a complex problem, and they are actively studied and addressed by different approaches such as [2,3,4,5], to name a few here. In the presented work, we focus on the multi-robot coordination strategy in communication-restricted environments, where an explicit exchange of large data volumes is not possible because of limited bandwidth.

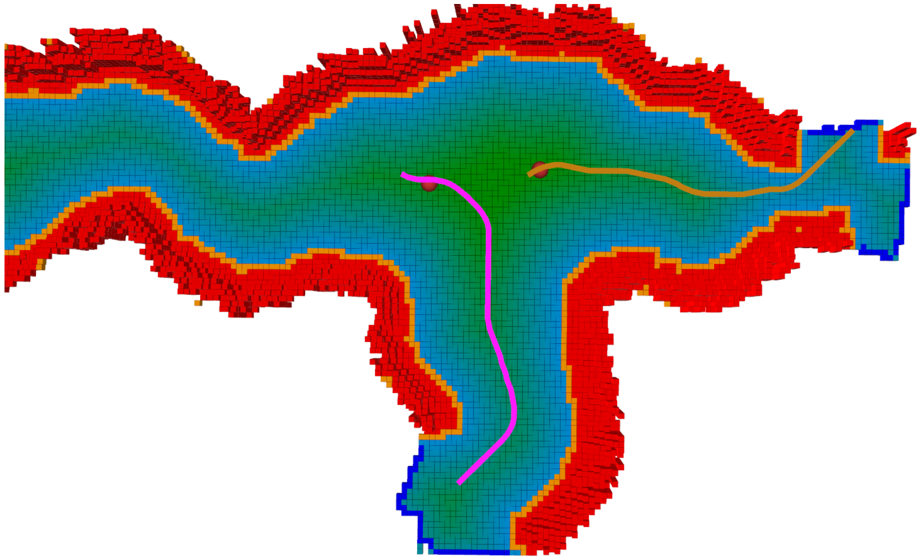

Fig. 1: An example of the robots' goal locations assigned by the proposed approach in the multi-robot exploration of the simulated cave environment.

The coordination strategy is especially crucial for environments where loops are rare such as caves or gold mines. In these environments, inappropriate decisions might result in undesired returns of the robots, which increases the time needed to search the environment and puts additional stress on the endurance of the robots and their equipment. Therefore, it is important to efficiently coordinate the robot decisions and optimally distribute the robots across the environment without unnecessary returns. The decisions taken at the crossroads are of our particular interest as they represent critical parts of the environment. An example of the decision at the crossroad taken by the proposed task allocation method in the cave-like environment is illustrated in Fig. 1.

Coordination of multiple robots in autonomous explorations has been addressed by various approaches [6,7,8,9,10,11]. Existing centralized approaches rely on the global map of the explored environment from particular robots or on sharing maps of the environment, which puts relatively high requirements on the communication reliability and bandwidth. In the studied exploration of underground environments, communication is considered unreliable, and its bandwidth very limited [12]. Therefore, we propose to address the robot coordination under unreliable and low bandwidth communication capable of broadcasting less than $100\,\mathrm{B\,s^{-1}}$ from each robot, similar bandwidth to [13], and lower than utilized in [4]. Such communication is not suitable for sharing the whole models of the environment perceived by the robots, but it is sufficient for sparse sharing of the robots' positions.

In the proposed multi-robot exploration, the coordination of the robots during the exploration mission is addressed as a solution to the task allocation problem, where each robot decides where to go next based only on its model of the environment and its knowledge of other robots' positions collected from the beginning of the mission. The proposed decentralized task allocation algorithm is not limited to a particular method of determining possible goal locations being assigned to the robots. Various approaches can be utilized to generate goal candidate locations, including frontier-based approaches [14], the uncertainty of the model [15], and entropy [16]. The goal candidates can also be generated as described in [3] or as the locations for exploring combined spatial and traversability terrain models [17]. Hence, the presented decentralized task allocation algorithm represents a framework for decentralized coordination of multiple robots in various multi-robot exploration setups.

The rest of the paper is organized as follows. An overview of the related multi-robot coordination approaches in exploration missions is summarized in the following section. The addressed problem is specified in Section 3, and the proposed decentralized task allocation algorithm is presented in Section 4. Evaluation results are reported in Section 5. The paper is concluded in Section 6.

## 2 Related Work

Autonomous exploration is an active research topic studied on various types of robots, including wheeled and tracked platforms [12], walking robots [5,18], small aerial vehicles [19,20], or even centaur-like platform [21]. The DARPA Subterranean Challenge [1] attracts significant attention to search the underground environments like mines, complicated urban structures, and caves for artifacts to identify limits of the existing technologies in autonomous exploration missions in challenging environments without the direct support of the communication infrastructure nor global satellite localization. In such environments, multi-robot exploration faces many difficulties induced by imperfect sensing and poor signal propagation, which is particularly addressed in this paper.

In the early multi-robot approach [7], the robots share the occupancy maps and select targets based on frontier cells [22] validated by a utility function. The initial ideas have been further improved by various approaches such as segmentation of the environments [8]. Different strategies of bidding on targets generated based on obtainable information have been investigated [9]. In the centralized approaches [10,11], the K-means algorithm can be deployed to divide the environment into regions for each robot. However, all these approaches require sharing the occupancy maps between the robots or a central unit capable of allocating tasks for each robot. If the occupancy maps cannot be shared between the robots because of limited communication bandwidth, these methods cannot be used effectively. Furthermore, it is also the case of the approaches for communication-restricted environments [23] that address the problem of maintenance of the connectivity between the robots.

The low bandwidth communication requirements have been addressed in [24], where the authors propose to share maps represented by sets of polygons to lower requirements on the communication. In [4], the authors propose to compress the shared maps by the occupancy normal distributions transform. On the other hand, the MinPos method [25] addresses limited communication differently. The authors propose a task allocation strategy based on ranks of all positions goal locations to evaluate their importance with respect to each robot $r$. In [25], the rank of the $j$-th possible goal location for the robot $r$ is computed as

$$G_{j,global}^{\mathrm{MinPos}} = \sum_{\forall R_k \in (\mathbf{R} \setminus \{r\}), C_{k,j} < C_{r,j}} 1, \tag{1}$$

where $\mathbf{R}$ is the set of all robots, and $C_{k,j}$ is the length of the path between the $k$-th robot and $j$-th possible goal location. Although the precise computation of $C_{k,j}$ requires sharing maps between the robots, if the path lengths are approximated, MinPos provides a solution to the task allocation even in the case maps are not shared. Therefore, the proposed decentralized task allocation is based on the MinPos approach that is further developed for the setups without sharing the maps but with a sparse exchange of the robots' positions.

## 3 Problem Statement

The scope of the paper is limited to the task allocation problem, and the necessary building blocks of the exploration, including localization, mapping, and navigation, are considered to be sufficiently solved [12]. Thus, each robot can localize itself during the mission within the common coordinate frame established at the beginning of the mission as it is done in the DARPA SubT Challenge [26]. The proposed task allocation is independent of how possible goal locations are determined; however, we employ the idea of the clustered frontiers [14] for the herein presented results. The addressed decentralized task allocation algorithm is highlighted within the context of the whole exploration system in Fig. 2.

The particular assumptions with their implications are as follows.

1. Robots are localized within the same coordinate frame established at the beginning of the mission, where the individual localization systems are initialized to have the common origin at the exact absolute location defined by the entrance to the mission area. *It allows sharing the individual pose estimates of the robots within the common coordinate frame.*
2. Robots cannot block each other while passing the corridor considered sufficiently wide. *It allows simplifying the navigation and also estimation of the average speed of the robots.*
3. Robots are moving through the environment at a similar speed. *It simplifies the prediction of the travel cost using the same motion model for all robots.*
4. Potential goals are removed from the individual robot's list when they are reached or when the robot unsuccessfully tries to reach them. *The assumption is to avoid the cases when a robot is stuck at some position because its navigation system cannot reach the current selected goal, or the goal is repetitively provided as the next possible goal even though it has been already reached.*

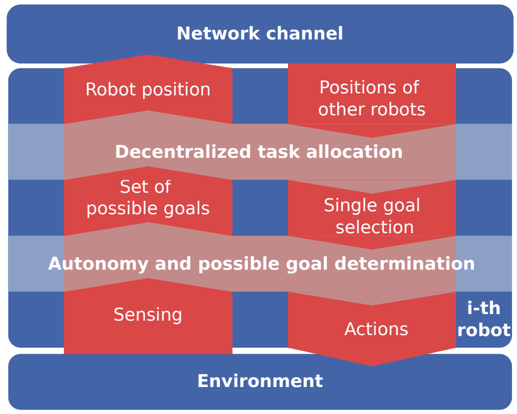


Fig. 2: Schema of the employed exploration system utilized for the evaluation of the proposed decentralized task allocation.

The inputs of the addressed task allocation problem are: (i) a set of potential goal locations; and (ii) pose estimates of all robots. The output is a single goal location towards which the particular robot is navigated until its next goal location is determined. The robot stops the exploration when no potential goal location is available. The performance of the proposed exploration strategy and comparison to the baseline approaches is achieved by evaluating the whole exploration system using lengths of the traveled paths by the robots during simulated exploration missions.

The traveled paths in the simulations are selected to make the evaluation independent of the available computational resources, demands of the utilized environment representation, and implementations of the particular modules of the whole exploration framework. The overall performance of multi-robot exploration is indicated by the average longest traveled path

$$p_{max} = \frac{1}{L} \sum_{l=1}^{L} \left( \max \left\{ p_{1,l}, \ldots, p_{n,l} \right\} \right), \tag{2}$$

where $p_{i,l}$ is the length of the $i$-th robot's path, $n$ is the number of robots, and $L$ is a number of performed trials for a particular evaluation scenario. The longest traveled path indicates how efficiently the robots are distributed in the environment. Considering the similar average speed of motion, it also indicates the time to finish the exploration mission. Thus, the exploration strategy is considered better for lower values of the $p_{max}$ indicator. In the evaluation results presented in this paper, the environment is considered explored if the union of the individual environment models of all robots covers the whole environment, i.e., all parts of the environment have been visited by at least one robot.

## 4 Proposed Decentralized Task Allocation Algorithm

The proposed task allocation algorithm follows the idea of MinPos [25] that computes ranks of all potential goal locations to evaluate their importance. For simplifying the notation, the set $\mathbf{R}$ of all $n$ robots is split into the actual robot $r$, for which we are computing the ranks, and the set of the remaining $m = n-1$ robots $\mathbf{R}' = \mathbf{R}\backslash\{r\}$. We further propose to calculate the ranks from two parts, each responsible for the different behavior of the robot. The rank $G_{j,rank}$ of the $j$-th potential goal at the corresponding location $\mathbf{p}_j \in \mathbb{R}^3$ is computed as

$$G_{j,rank} = G_{j,global} + G_{j,local}. \tag{3}$$

The first part of (3) follows the MinPos ranking (1), which counts how many of the robots $\mathbf{R}'$ have a shorter path to the $j$-th goal than the actual robot $r$. Thus, $G_{j,global}$ is responsible for the global distribution of the robots among the mission area so that the $r$-th robot tries to get as far from other robots as possible using only the most recent positions of the robots. For the proposed ranking, we approximate true path lengths by the Euclidean distance $\|\cdot\|$ between the robots and potential goal location because paths nor full environment map are not available due to limited communication. The computed Euclidean distances between two selected locations provide similar results when computed by different robots. The proposed global rank is computed as

$$G_{j,global} = \frac{\min\left(\sum_{k=1}^{m} \frac{\|\mathbf{p}_j - \mathbf{r}\|}{\|\mathbf{p}_j - \mathbf{h}_{k,\zeta}\|}, m\right)}{m}, \tag{4}$$

where $\mathbf{r} \in \mathbb{R}^3$ is the current position of the $r$-th robot and $\mathbf{h}_{k,\zeta}$ is the most recently received position of the $k$-th robot from $\mathbf{R}'$. The impact of the simplified (4) compared to the original MinPos algorithm [25] is evaluated in Section 5.

The second term $G_{j,local}$ enables the robot to select suitable direction at the crossroads by penalizing goal locations based on the visited locations by the robots $\mathbf{R}'$ that are estimated from their received positions since the start of the exploration mission. The local rank $G_{j,local}$ is computed as

$$G_{j,local} = \sum_{k=1}^{m} \left(1 + \operatorname{sign}\left(m_r - \left\|\mathbf{p}_j - \operatorname*{argmin}_{\mathbf{h_{k,l}} \in \mathbf{H}_k}(\|\mathbf{h}_{k,l} - \mathbf{p}_j\|)\right\|\right)\right), \tag{5}$$

where $\mathbf{H}_k$ is the set of all positions of the $k$-th robot from $\mathbf{R}'$ received by the robot $r$, and the thresholding parameter $m_r$ limits the distance from the recorded robot positions on which the ranks of potential goals are increased. For addressed subterranean environments, we empirically found a suitable value of $m_r$ to be set between half of the tunnel width and the distance between tunnels entrances at the crossroads if these parameters are known. If such information is not available, the value of $m_r$ should be higher than the largest robot dimension.

The resulting goal is selected as the potential goal location with the lowest rank computed by (3). If multiple goal locations have the same rank, the location reachable by the shortest path is selected as the final goal. Here, it is worth noting that the ranking is designed so that the local part of the rank $G_{j,local}$ always overpowers the global part $G_{j,global}$ if there exists a robot in $\mathbf{R}'$ that is closer to the potential goal $j$ than $m_r$.

Regarding the computational complexity, the complexity of the proposed rank (3) is proportional to all received positions of robots from $\mathbf{R}'$. Contrary, the computational complexity of each MinPos rank (1) is proportional to the number of robots $n$ and the complexity of computing path lengths from the robot positions to each selected goal location. Thus, MinPos might be more demanding because the proposed method employs quickly to compute Euclidean distances.

## 5 Results

The performance of the proposed ranking-based task allocation algorithm has been empirically evaluated in three simulated environments. The S.T.D.R. Simulator [27], capable of simulating multiple robots in real-time, has been utilized for all the presented results. The autonomous behavior for each exploring robot, including navigation to the selected goal location, has been provided by the exploration system [18]. The system incrementally builds an elevation map [28] from the 3D scans paired with the 6 DOF robot poses. The possible goal locations are determined using clustered frontier cells as in [29,30].

The simulated robots were operated in the planar simulated environment by the forward and angular velocities generated by the autonomous exploration framework [18]. Each robot was equipped with the omnidirectional LiDAR with a range limited to 10 m providing laser scans at the height of 0.5 m above the terrain with the frequency of 5 Hz. The simulator provided the 6 DOF localization of the robots within the frame of the simulated environment. Since (3) requires an exchange of 3 DOF position $\mathbf{p} = (p_x, p_y, p_z)$, the positions are extracted from the 6 DOF localization and shared between the robots as 3 floats (12 B) at the frequency of 1 Hz.

Three testing environments S1, S2, and S3 are based on the virtual cave circuit environments of the DARPA Subterranean Challenge have been utilized for the empirical evaluation. In each environment, three different placements of the robots have been considered, which gives nine exploration setups in total, see Fig. 3. The robots are placed in the start area in the first placement and randomly in two other placements. Furthermore, for each evaluation scenario and each task allocation algorithm, the exploration mission is performed in two evaluation trials. In all scenarios, the team consists of five exploring robots.

The proposed task allocation algorithm, denoted as **Proposed**, has been compared with the greedy task selection denoted **Greedy**, the original **MinPos** [25] with the enabled sharing of the maps between the robots and computing the rank using path lengths in (1). Besides, we examine the influence of the MinPos ranking computed using the proposed (4) and not from the path lengths to examine the benefit of the proposed local part (5). Such a modified MinPos is denoted **Global**. In **Greedy**, the closest goal location to each robot is selected

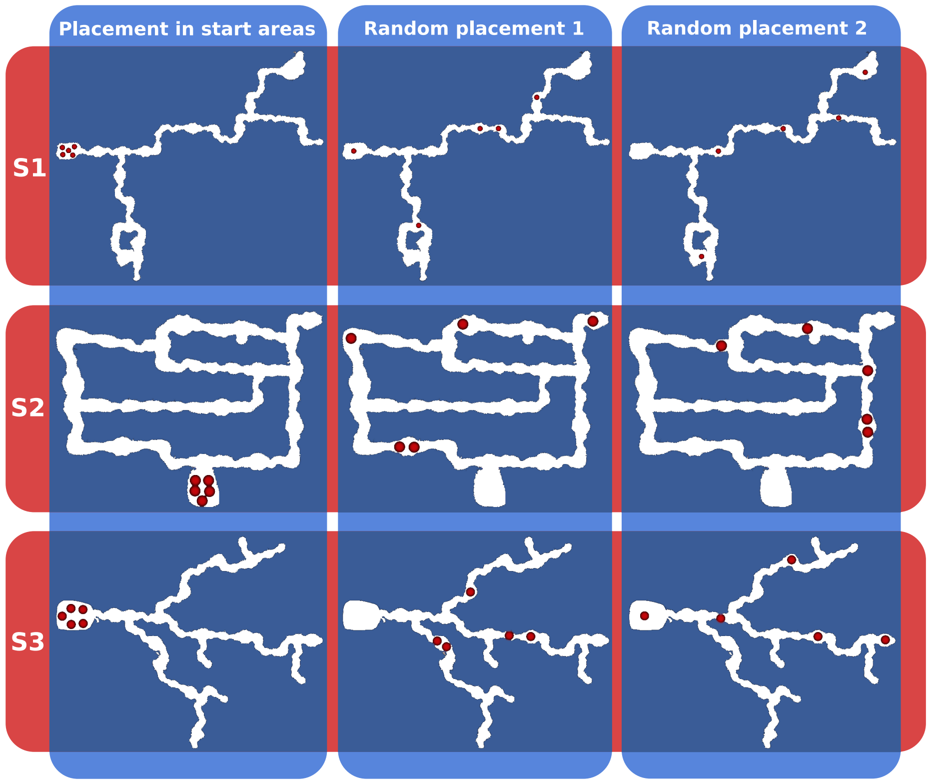


Fig. 3: Testing environments S1–S3 utilized in the empirical evaluation. The small red disks denote the initial robot positions.

without considering any information from other robots. The simulation results are summarized in Table 1, and examples of the robot paths for the proposed method in each environment are shown in Fig. 4.

### 5.1 Discussion

The results in Table 1 show that the **MinPos** and the proposed task allocation algorithms perform better than the **Greedy** approach. It can be seen **Global** outperformed the **Greedy** approach using the approximation of true path lengths by Euclidean distance. However, in most cases, **Global** is worse than **MinPos** because of the wrong decisions taken at the crossroads, which is the motivation for adding the term (5). The only exception where **Global** performed better than **MinPos** is the last scenario S1 with the initial placement of the robots at the entrance, where the geometry of the environment led to the have similar decisions made by **Global** and **Proposed**.

A huge gap between the **MinPos** and **Proposed** methods can be observed for the S1 scenario with random placement of the robots. It is because of (4)

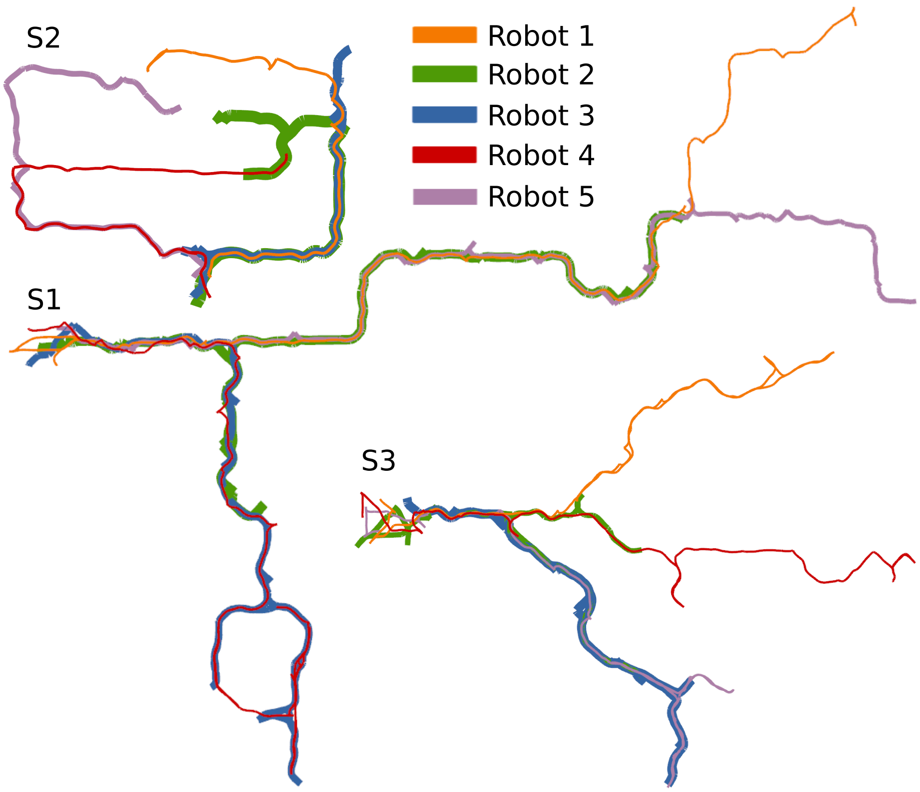


Fig. 4: Example of the robot paths in multi-robot exploration using the proposed task allocation algorithm for scenarios with the initial placement of the robots at the entrance to the underground environment.

that ensures the robot prefers potential goal locations that are farther from other robots if the robot is far from the others. Therefore, the robots tend to spread and visit far locations from the very beginning. On the other hand, if there are two potential goal locations close to the robot that is far enough from the rest of the robots, **MinPos** selects the next goal based on the length of the path to the goals, which is similar to the greedy task allocation.

The proposed method is designed to prefer a selection of the not visited areas at the crossroads (see Fig. 4) and try to get as far from the other robots as possible, which is supported by the improved performance for the S3 environment. However, since the proposed method is not sharing the maps, crossing the already visited parts of the environments to uncover parts unknown to all the robots takes more time, which can be seen for the S2 testing scenario.

During the empirical evaluation of the proposed method, we investigated its sensitivity to the value of the parameter $m_r$ that can be reduced by similar behavior of the robots in the same part of the environment, such as the cases

Table 1: Performance of Task Allocation Methods in Multi-robot Exploration.

| Testing Scenario | Initial Robot Placement | $p_{max}$ [m] Greedy | MinPos | Global | Proposed |
|---|---|---|---|---|---|
| S1 | Random | 228.2 | 193.0 | 201.2 | **130.8** |
| | Entrace | 482.8 | 265.9 | 400.1 | **243.6** |
| S2 | Random | 107.9 | **63.2** | 78.3 | 66.2 |
| | Entrace | 136.6 | **89.8** | 115.4 | 103.2 |
| S3 | Random | 169.1 | 139.0 | 160.3 | **134.8** |
| | Entrace | 348.5 | 200.6 | 188.5 | **188.5** |

when the robots are navigated through the corridor center, and the possible goal locations are placed in the corridor centers as well. Thus, the performance can be further tuned by the particular choice of how possible goal locations are determined. Besides, deadlocks or cyclic revisiting of the same areas by robots driven by any examined methods have not been observed. Overall, based on the results, the proposed ranking computation shows be a suitable option if limited computation does not allow the exchange of large data between the robots.

## 6 Conclusion

In this paper, we present a novel decentralized task allocation algorithm for multi-robot exploration with limited communication. The presented results support the feasibility of the proposed approach that outperforms greedy goal assignment. Furthermore, the results indicate improvement of the exploration performance over the original MinPos method in one of three evaluation scenarios. Moreover, the proposed method is less demanding than MinPos, since it does not require knowing the paths between all potential goal locations and the robots. The performance of the proposed method might be further improved by sharing maps between the robots if communication bandwidth would allow that. However, packet losses might be encountered in real-world scenarios that we aim to address in our future work. Besides, we plan to improve the performance of the exploration method in scenarios with significant localization drift and heterogeneous robots.

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