Multi-Robot Exploration without Explicit Information Exchange

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***Abstract*— In this paper we present a novel method to coordinate a team of multiple robots in a frontier-based exploration task that leverages wireless signals to retrieve relative positions, and weights information gain for different frontiers accordingly. Previous multi-robot frontier-based exploration methods depend on explicit information exchange amongst robots such as a shared global map or realtime position exchanges. We do not rely on explicit information exchange and instead use range and bearing extracted directly from wireless signals that allow robots to estimate relative positions of their neighbors within the team, even in non-line-of-sight scenarios. Our method shows that even without a centralized system, and without explicit information exchange, a team of multiple robots can coordinate exploration using these relative positions in order to minimize simultaneous overlap of their individual explored regions. We validate our proposed algorithm on real robots in cluttered 300m^2 environment as well as in simulation.**

I. Introduction

Efficient exploration of unknown environments using a multi-robot team is dependent upon how well the team of robots can coordinate. A commonly used approach for achieving multi-robot exploration in such environments is frontier-based exploration [1]. Frontiers, defined as the boundaries between known and unknown regions of an environment [2], are visited and explored by robots in a team until the entire space has been explored. This often requires robots to explicitly share information such as their map, landmark features, or relative positions in a common reference frame. However, reliance on such information exchange often requires external infrastructure such as a GPS, overlapping map features, and/or visual contact between robots. These requirements thereby limit the environments robot teams may operate in, particularly in communication constrained or non-line-of-sight (NLOS) environments.

In this paper, we instead seek to enable multi-robot frontier-based exploration using only *implicit information exchange*. We assume that agents have access only to measurements acquired via on-board sensors, and that they can sense noisy range and bearing information of other robots using Ultra wide band (UWB) and WiFi signals. In this method, *robots rely only on their local map and indirect measurements of other robots' relative positions to modify their own exploration strategy and achieve efficient team-wide exploration.* Hereafter, we refer to this as exploration with implicit information exchange.

In frontier-based exploration, a robot visits frontiers in the order of their utility value, i.e., frontiers with high information gain and minimal travel cost are prioritized [3]. Traditionally, efficient exploration is achieved by delegating frontiers to each robot systematically. In order to achieve this, *explicit* knowledge of common frontiers and relative positions of robots within the team is critical. Thus, in order to enable coordinated multi-robot exploration without explicit information exchange we must address the following challenges:

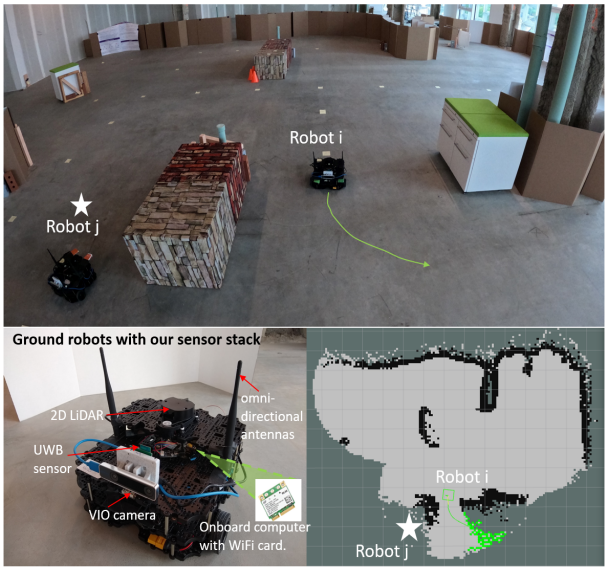

Fig. 1. *Schematic showing our proposed frontier-based exploration algorithm. By locally estimating the relative positions of its neighbors, a robot can modify the choice of frontier to navigate to for reducing simultaneous exploration overlap.*

1) **Relative position estimation in NLOS:** A robot needs to obtain the relative position estimates of its neighbors locally without a global map or reference frame in both communication constrained and NLOS scenarios.
2) **Frontier selection using implicit coordination:** A robot's frontier-based exploration algorithm should incorporate only local information while minimizing simultaneous exploration (overlap) of regions in the environment with other robots.

Estimating positions in NLOS necessitates the usage of new sensing modalities beyond vision based onboard sensors. Wireless signals have been widely explored in robotics for various applications, such as localization [4], rendezvous [5], [6] and SLAM [7], among others. Since these signals can pass through walls and other occlusions, they can be used effectively in NLOS. Additionally, they require only minimal data transfer (e.g., ping packets), which can be broadcasted. Thus, we address the first challenge by enabling robots to obtain relative position estimates of their neighbors using commercial off-the-shelf onboard wireless signal-based sensing modalities. The positions are obtained by combining range estimates from the Ultra Wide Band (UWB) sensor and bearing estimate from the WSR toolbox [8]. This approach however, suffers from the non-trivial *multipath problem*. This

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occurs when transmitted wireless signals physically interact with their environment, where they may attenuate and/or scatter, and can appear to arrive from different locations [9]. The multipath problem leads to inaccurate range and bearing measurements resulting in spurious position estimates. To address this, we leverage a key observation — given small local motions of the robot platforms, the angle-of-arrival (AOA) measurements arising from scattering should change more sporadically than the direct-line AOA between two robots [10]. Thus, we filter for measurements that have undergone minimal change during the short sampling duration as top candidates for direct-line AOA measurements. The position estimates arising from these filtered measurements are then iteratively refined using a particle filter [11] to reduce false positives and return the most likely estimate at each timestep.

To address the second challenge, we develop a heuristic-based, myopic frontier-based algorithm. We build off of work such as [12], which calculates a frontier's utility as information gain (determined by the size of unknown region near the frontier) per unit of travel cost. Importantly, in order to achieve implicit coordination, we modify a robot's local utility computation by introducing bias terms based on the relative position estimates of its neighbors. These terms aim to minimize simultaneous overlap of robots' locally mapped regions. Additionally, if one or more neighbors of a robot are estimated to be closer to a robot's local frontier than itself, the bias terms account for potential redundant navigation effort which may result in reduced utility for that frontier (Figure 1).

We validate our proposed approach on actual robots operating in a 300 m^2 cluttered NLOS environment. Our position estimation method achieves 2.5 m median accuracy in NLOS and in presence of strong signal multipaths. When combined with our frontier-based exploration algorithm, it leads to higher reduction in simultaneous overlap of robots explored regions in contrast to an algorithm that does not incorporate these relative position estimates. To address autonomous exploration termination, we implement an oracle system which stops each robot's exploration when a certain percentage of the entire environment has been explored.

Contributions of this paper:

1) We obtain relative position estimates using onboard wireless signal-based sensors. Using a particle filter based approach, we reduce spurious estimates resulting from wireless signal multipaths.
2) We incorporate these relative position estimates in each robots' local frontier-based exploration algorithm to achieve implicit team-wide coordination.
3) We showcase the efficiency of our proposed system in hardware experiments with ground robots in 200 m^2 cluttered NLOS environment.

II. Related Work

Robots employ multiple strategies for exploration in unknown environments such as information theoretic methods [13] and frontier based [2], [14], amongst others. Work by Yamauchi [1] shows how robots can select different non-overlapping frontiers for coordinated exploration. Such a strategy requires access to information such as a common map and spatial positions of robots for efficient frontier generation and assignment, respectively. To address the limitations of centralized implementations [3], decentralized methods have been developed that rely on map sharing between robots [15]. However, communication constrained environments limit the amount of information that robots may communicate. To address the constraints on information sharing for *generating* frontiers, methods for multi-robot map merging have been recently proposed [16], [17]. However, obtaining an accurate global map using distributed methods is non-trivial in unknown environments [18]. As multi-robot exploration progresses, obtaining intermediate shared maps depends on access to common features between robots in order to enable loop closure. This requires substantial overlap between the explored areas of robots, even during the early stages of exploration. A few decentralized approaches assign separate sub-regions to each robot for exploration altogether [19], but this is not feasible in completely unknown environments.

Frontier *assignment* requires knowledge of the relative positions of the other robots, often inferred from shared maps [15], [20], [21]. Other decentralized methods use auctions [22], [23], [24], [25] but this requires substantial communication overhead and require robots to make synchronous decisions. Robot positions can also be inferred from localization based methods using wireless signals. However, distributed localization schemes require fusing multiple local coordinate frames into a single global coordinate frame. This requires synchronized communication between robots, continuous exchanges of local position estimates [26] as well as other information such as velocity and yaw [27].

In our system, we aim to address the limitations of these existing approaches. We allow robots to estimate relative positions of their neighbors locally without distributed localization or exchanging any heavyweight information. These estimates bias their local frontier-based algorithms to minimize simultaneous overlaps in explored regions with other robots. Similar methods exist that incorporate constraints in frontier-based exploration algorithms using positions of neighboring robots, but they require centralized planning [28] or global positions using distributed localization [29]. In addition to the above, we deploy our system in decentralized manner on real robots with noisy sensors. Each robot is equipped with single UWB sensor and commodity WiFi card that is used to obtain relative position estimates by exchanging lightweight "ping" packets that are ~ 60 bytes. Thus, robots only require their onboard sensors and computation to improve coordination.

III. Problem Statement

We consider a team $\mathcal{R} \subset \mathbb{R}^{1\times n}$ of homogeneous mobile robots exploring an unknown bounded 2D environment. Each robot $i \in \mathcal{R}$ is equipped with a finite-range $360°$ laser sensor, with scan radius r, to map the geometric structure of the environment. The map is represented as a 2D occupancy grid map denoted by $\mathcal{M} \subset \mathbb{R}^2$. Robots are also equipped with an onboard UWB and WSR Toolbox [8] in order to obtain inter-robot range and bearing measurements, respectively. A robot i can exchange "ping packets" with all robots in its

neighborhood and thus obtain inter-robot range and bearing measurements for them. We denote such a neighborhood of a robot i as $\mathcal{N}_i$. In this paper, we assume that any robot $i \in \mathcal{R}$ can obtain inter-robot measurements to all other robots i.e., $\mathcal{N}_i = \{j | j \in \mathcal{R}, j \neq i\}$.

The robots operate in a decentralized manner and do not have access to a shared or prior map. They also cannot rely on realtime inter-robot communication of data such as map updates or motion plans, due to communication constraints. The robot team also does not use any realtime localization methods as that would require inter-robot communication of data and synchronized behavior. Each robot can rely only on the local information from its on-board sensors and maintain a local coordinate frame of reference. Thus, we assume that each robot locally runs a Simultaneous Localization and Mapping (SLAM) [30] algorithm. Robots also have their own global/local path planners to enable navigation while avoiding collisions. Our goal is to enable coordinated exploration for a team of robots under these constraints and robots' local capabilities.

The first problem that we address for achieving our goal is estimating relative positions using robots' onboard wireless signal-based sensors only.

Problem 1. *Robot i needs to estimate relative positions $\hat{x}_j$ for all robots $j \in \mathcal{N}_i$ by combining range measurement $dist$ and bearing measurement φ obtained from onboard wireless signal based sensors. Additionally, $\hat{x}_j$ should be attainable even in presence of signal multipaths.*

Next, we need a frontier-based exploration algorithm that uses these relative positions and local map to achieve coordination during exploration. Given a local map $\mathcal{M}_i$ of robot i, a frontier $f_i \subset \mathbb{R}^{n \times 2}$ consists of n grid cells that are on the boundary of the known and unknown space in $\mathcal{M}_i$. $\mathbf{F}_i$ denotes the set of all such frontiers generated by robot i at time t. Robots compute a scalar *utility* value of all frontiers $f_i \in \mathbf{F}_i$ based on the number of new unknown grid cells that can be detected form frontier within scan radius r and the navigation effort to reach it. We thus define the information gain $\mathcal{I}_i^{f_i}$ as the number of unexplored cells within radius r from the center of a frontier. The effort $\mathcal{C}_i^{f_i}$ is defined as the euclidean distance between the robots current position and center of a frontier. Following the approach in [12], the utility $U_i^{f_i}$ of a frontier $f_i \in \mathbf{F}_i$ is defined as information gain per unit of effort. The total exploration duration is denoted by $\mathcal{T}$. Thus, the second problem that we solve is the following.

Problem 2. *Design a frontier-based algorithm such that at every timestep $t \in \{0 \ldots \mathcal{T}\}$, robot i navigates to a frontier $\hat{f}_i$ that has highest utility.*

$$\hat{f}_i = \arg\max_{f_i \in \mathbf{F}_i} (U_i^{f_i}), \text{where} \quad U_i^{f_i} = \mathcal{I}_i^{f_i} / \mathcal{C}_i^{f_i} \tag{1}$$

The utility calculation is modified based on estimated positions $\hat{x}_j$ for all robots $j \in \mathcal{N}_i$.

Thus, each robot i needs to select its local frontiers such that it minimizes simultaneous overlap of its explored regions with any robot $j \in \mathcal{N}_i$, leading to lower $\mathcal{T}$. By overlap we mean that the distance between any two robots is less than the scan radius r.

A related problem that the robot team R needs to address is about terminating exploration. Here, robots need to determine when to stop exploration, using only local information, by estimating the combined total coverage of their environment. We do not address this problem in the current paper. Instead we rely on an oracle system that tracks individual map coverage of each robot and issues the termination command to all robots when the environment has been sufficiently explored globally. We also assume that the final merged map can be generated after termination when robots exit the environment or via asynchronized intermittent access to a centralized server. [31].

Algorithm 1 Frontier exploration algorithm

Require: Local frontier set $\mathbf{F}_i$ of robot i, bearing measurements in 2D ϕ from WSR Toolbox, distance measurements D from UWB sensor
while Select next frontier **do**
  for $\forall d \in D, \forall \varphi \in \phi$ **do** ▷ step 1
    $\hat{\chi}_{\mathbf{j}}(\mathbf{t}) \leftarrow [dist * cos(\varphi), dist * sin(\varphi)]$
  end for
  Particle filter $\leftarrow \hat{\chi}_{\mathbf{j}}(\mathbf{t})$ (Eqn:2) ▷ step 2
  $\hat{x}_j \leftarrow x_j^{[m]}$with max $w_j^{[m]}(t)$
  for $f_i \in \mathbf{F}_i$ **do** ▷ step 3
    $\mathcal{I}_i^{f_i} \leftarrow$ Information gain(Eqn: 4)
    $\beta \leftarrow$ Information gain overlap (Eqn: 5)
    $\mathcal{C}_i^f \leftarrow ||x_c^f - x_i||$
    $\gamma \leftarrow$ Redundancy in navigation effort (Eqn: 6)
    $U_i^f = \beta \mathcal{I}_i^f \Big/ \mathcal{C}_i^f (1 + \gamma)$
  end for
  Next frontier$\hat{f}_i = \arg\max_{f_i \in \mathbf{F}_i} (U_i^{f_i})$
end while

IV. Proposed approach

Our goal is to enable a team of robots to efficiently explore an unknown environment while coordinating implicitly. To achieve this goal, each robot uses a myopic frontier-based exploration method. Each robot runs an onboard SLAM algorithm to generate a local map $\mathcal{M}$ and obtains the frontier set $\mathbf{F}_i$ at every timestep t. Robot i then locally obtains relative position estimates of all robots in $\mathcal{N}_i$ (Sec IV-A). The proposed algorithm uses this information to set a utility value to each frontier (Sec IV-B). The robot then navigates to the frontier with the highest utility and repeats this process until the termination signal is triggered (Sec V-C).

A. Obtaining Relative Positions

To obtain $\hat{x}_i$ for a robot $j \in \mathcal{N}_i$, robot i fuses data from its onboard UWB sensor and the WSR toolbox. Due to the multipath phenomenon, the signal can to appear to arrive from several different locations. Figure 2 shows the position estimation pipeline. Robot i uses the WSR toolbox to obtain multiple bearing observations $\varphi \in \phi$ for a robot j over a short sampling duration. These bearing measurements are then compared in order to extract those that have undergone minimal change. We leverage the fact that bearing from multipath will vary randomly while bearing from direct signal path does not [10]. The UWB sensor returns multiple range measurements; we uniformly sub-sample from this. Each filtered bearing measurement is then combined with

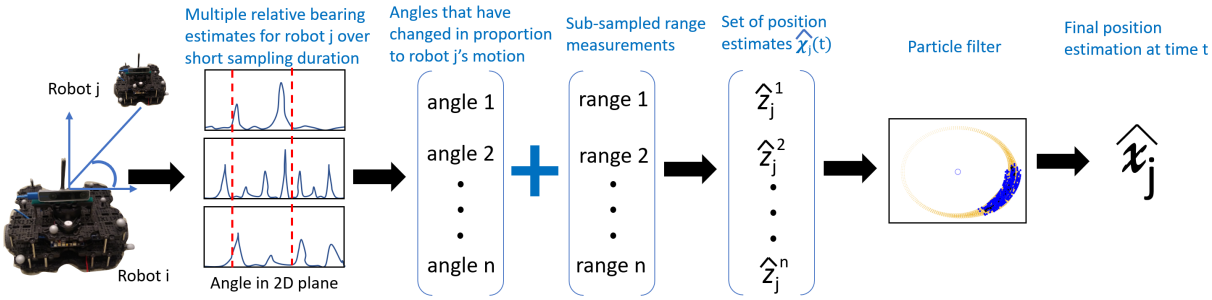

Fig. 2. *Position estimation pipeline schematic. Robot i combines the bearing and range measurements to robot j, sampled over a duration of 10 seconds (See Alg. 1). The estimates are iteratively refined using a particle filter to get the best position estimate of robot j.*

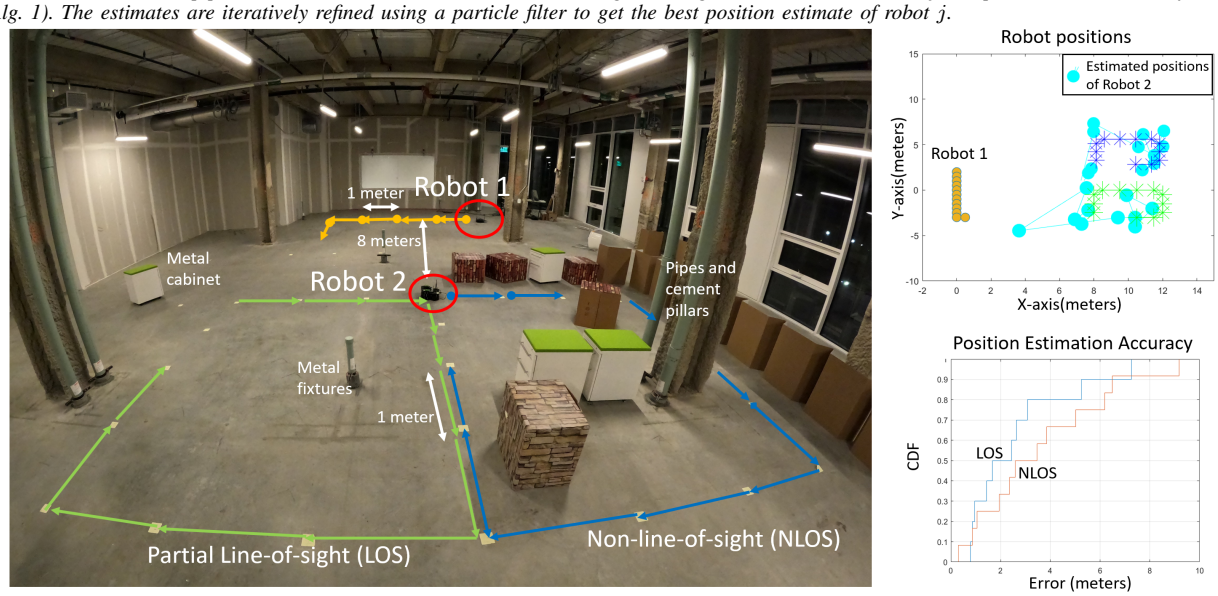

Fig. 3. *Hardware experiments showing the accuracy of relative position estimation using our method. Robot 1 (moving along the yellow trajectory) collects range and bearing measurements of robot 2. By combining these measurements to estimate relative position as shown in Figure 2, we achieve 2.2m median accuracy in NLOS heavily cluttered environment. The blue and green asterisks in the top right plot denote true positions of robot 2.*

every sub-sampled range measurement to generate a set of position estimations $\hat{\chi}_{\mathbf{j}}(\mathbf{t})$ at time t (Algorithm. 1, step 1).

To further improve position estimation, we use a standard particle filter algorithm (Table 4.3, [11]). The m_{th} particle sample $x_j^{[m]}(t)$ for robot j at time t is is generated uniformly around $x_j^{[m]}(t-1)$ at distance d as we assume that velocity of robot j is known. The weight of this particle, $w_j^{[m]}(t)$, is calculated as

$$w_j^{[m]}(t) = \frac{1}{k}\sum_{n=1}^{k} e^{\frac{-\left\|\hat{z}_j^n - x_j^{[m]}(t)\right\|}{2}} \tag{2}$$

where $\hat{z}_j^n \in \hat{\chi}_{\mathbf{j}}(\mathbf{t})$ for $n \in [1..k]$, k is cardinality of $\hat{\chi}_{\mathbf{j}}(\mathbf{t})$ and $\|.\|$ denotes euclidean norm. New particles are then resampled based on these weights and the particle with the maximum weight is returned as $\hat{x}_j$.

B. Frontier Exploration Algorithm

In our proposed frontier-exploration algorithm (Algorithm 1), each robot uses information of its relative position to its neighbors, as well as navigation cost and information gain, to assign utility values to its generated local frontiers. Our baseline frontier-exploration algorithm follows the approach in [12], in which the utility $U_i^{f_i}$ for a frontier f_i is calculated as the information gain at the frontier per unit of effort (i.e. navigation cost) made by the robot i to reach said frontier (we drop the subscript i in f_i for brevity in the equation).

$$U_i^f = \beta \mathcal{I}_i^f \Big/ \mathcal{C}_i^f (1+\gamma) \tag{3}$$

Here, $\mathcal{I}_i^f$ denotes the information gain at the frontier and $\mathcal{C}_i^f$ denotes the effort to reach the frontier. Parameters β and γ account for the impact of the neighboring robots $j \in \mathcal{N}_i$. Formulations for each these variable are described hereafter.

1) Information gain: The net information gain $\mathcal{I}_i^f$ is calculated as

$$\mathcal{I}_i^f = \sum_{c \in E_f} a + (1-a)e^{-q g_t(c)} \tag{4}$$

where q is the decay rate. Because the local map of each robot is a grid map, c represents an unexplored grid cell such that $d_{fc} \leq r$ where r is the sensing radius and $d_{fc} = ||x_c^f - x_c||^2$ denotes the distance of cell c from the center of a frontier $f_i \in \mathbf{F}_i$. E_f is a set of such cells for each frontier f_i. $\mathcal{I}_i^f$ thus represents the unexplored region that robot i can sense when it reaches the frontier f_i. The information value for all unexplored cells c in robot i's local map is initialized to 1. At any time t, the expected information gain from an unexplored cell c is given by a which is calculated as

$$a = \begin{cases} 1 & g_t(c) = 0 \\ 0 & g_t(c) > 0, \end{cases}$$

$$\text{where } g_t(c) = g_{t-1}(c) + \sum_{j \in \mathcal{N}_i} k_j.$$

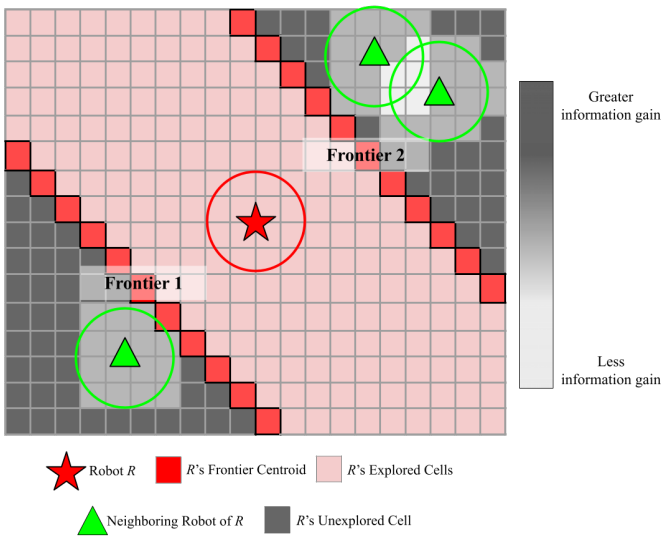

Fig. 4. Although equidistant from equal-sized frontiers F_1 and F_2, robot R (red star) will experience greater sensing overlap with other robots, and thus lower information gain, at F_2 than at F_1. Thus, robot R is likely to calculate F_1 with a higher utility.

$g_t(c)$ accounts for the total overlaps between the sensing radii r of robots at the cell c from time 0 to t. Note that t is robot i's local timestep, and it represents each time before a frontier is selected. At time t, k_j denotes the overlap, and is calculated as

$$k_j = \begin{cases} 1 & \text{if } d_{fc} < r \quad \text{and} \quad \hat{d}_{jc} < r \\ 0 & \text{otherwise,} \end{cases}$$

where $\hat{d}_{jc} = ||\hat{x}_j - x_c||^2$ denotes the distance of cell c from robot $j \in \mathcal{N}_i$, respectively, at the current time t. Thus, equation (4) leads to exponential decay of the information of each unknown cell c with increase in the number of calculated overlaps. Figure 4 demonstrates how robot i may account for overlap. Greater overlaps with other robots within a frontier will decrease that frontier's utility.

Additionally, the parameter β accounts for the overall proximity of f_i to all robots $j \in \mathcal{N}_i$ and is given as

$$\beta = \log(\sum_{j \in \mathcal{N}_i} ||x_c^f - \hat{x}_j||^2) \tag{5}$$

β makes a frontier more desirable for robot i, in terms of information gain, if it away from other robots in general. Figure 5 represents robot i weighting a frontier higher based in its proximity to other robots. Even if the current frontier has a low density of overlaps, i will also account for overlaps in future frontiers formed around the current frontier.

2) Navigation effort: $\mathcal{C}_i^f$ in equation (3) denotes the effort that robot i requires to reach a frontier's center. We use the euclidean distance to approximate this effort. Thus, $\mathcal{C}_i^f = ||x_c^f - x_i||$, where x_c^f is the position of the frontier's center and x_i is the robot i's current position. However, robot i could end up making a redundant effort if there is at least one other robot $j \in \mathcal{N}_i$ which robot i estimates to be much closer to f_i than itself i.e., $\mathcal{C}_i^f > ||x_c^f - \hat{x}_j||^2$. This is because such a robot j would reach an area around f_i faster and explore it before robot i can reach f_i (assuming the worst case scenario in which robot j indeed chooses to behave accordingly). On the other hand, if there is no robot j for which $\mathcal{C}_i^f > ||x_c^f - \hat{x}_j||^2$, then robot i's effort will not be

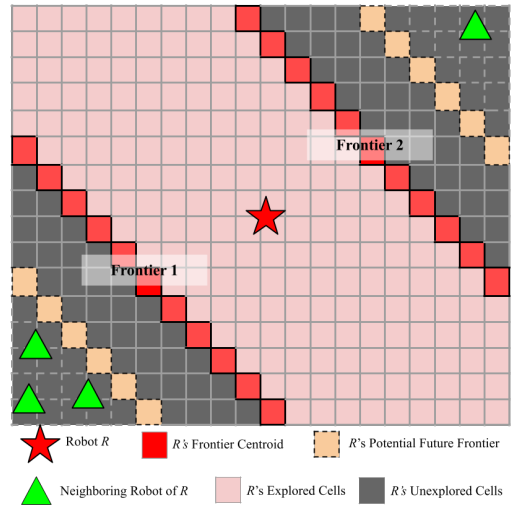

Fig. 5. Robot R is equidistant from equal-sized frontiers F_1 and F_2. However, there is a greater density of robots beyond F_1 than beyond F_2, which may diminish future information gain. Thus, β accounts for future information gain within the utility calculation such that robot R will calculate F_2 with a higher utility.

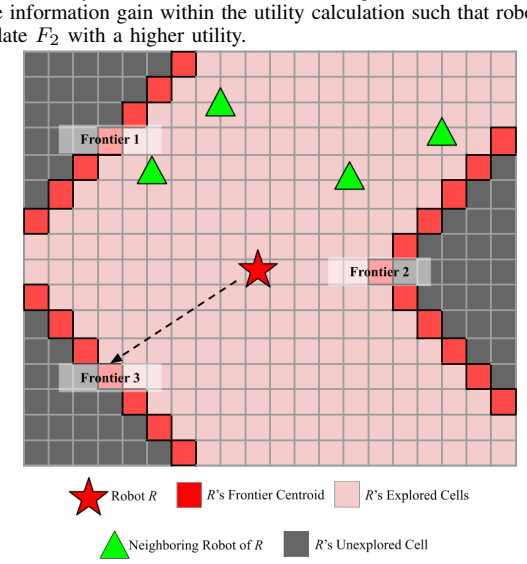

Fig. 6. In calculating the utility of frontiers F_1, F_2, F_3, robot R accounts for the distance between its neighboring robots and those frontiers. In this scenario, the proximity of the neighboring robots to frontiers F_1 and F_2 will increase the redundancy in R's effort to travel to those frontiers. Thus, robot R is likely to choose to navigate to F_3

redundant as it would likely reach f_i faster. To capture this redundancy of effort, we introduce the parameter γ_2 which is given as

$$\gamma = \begin{cases} 1/(1 + \widehat{\mathcal{C}_j^f}) & \widehat{\mathcal{C}_j^f} \leq \mathcal{C}_i^f \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$\text{where } \widehat{\mathcal{C}_j^f} = \min_{j \in \mathcal{N}_i} (\eta \mathcal{F}(f_i, \hat{x}_j))$$

$$\text{and } \mathcal{F}(f_i, \hat{x}_j) = \min_{\tau \in f_i} (||x_\tau^f - \hat{x}_j||^2)$$

τ denotes a frontier cell belonging to the frontier f_i. $\mathcal{F}(f_i, \hat{x}_j)$ denotes the minimum estimated euclidean distance i.e., the effort any robot $j \in \mathcal{N}_i$ needs to make before it reaches the robot i's frontier f_i. $\widehat{\mathcal{C}_j^f}$ denotes the minimal estimated effort the closest robot $j \in \mathcal{N}_i$ needs to make to reach the local frontier f_i of robot i. We specifically use use min of $\mathcal{F}(f_i, \hat{x}_j)$ to obtain $\widehat{\mathcal{C}_j^f}$ because even a single robot

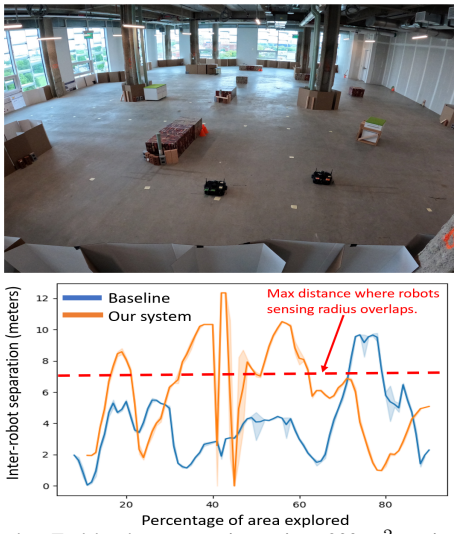

Fig. 7. End-to-End hardware experiment in a 300 m^2 environment. One of the robots is deployed with our system and has the capability to obtain relative position estimates of the other robot. For the trial with our system active, robots maintain a higher inter-robot distance for the majority of the exploration task, thus minimizing simultaneous exploration of same areas, i.e. minimizing sensing radius overlap, by the robots.

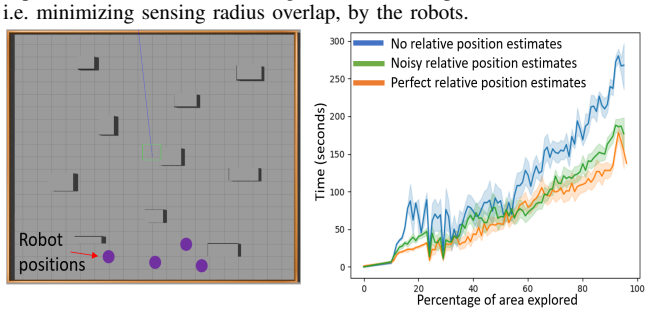

Fig. 8. Simulation showing the scalability of our proposed frontier-based exploration algorithm. With more robots capable of sensing even noisy relative positions of their neighbors using onboard sensors, exploration efficiency can be improved.

j closer to f_i than i is sufficient to make robot i's effort redundant. Thus, γ_2 denotes the redundancy in effort made by robot i if $\widehat{\mathcal{C}_j^f} \leq \mathcal{C}_i^f$ i.e., given that there exists at least one robot j for which $\mathcal{F}(f_i, \hat{x}_j) \leq \mathcal{C}_i^f$. As a result, the parameter γ_2 can lead to a reduction in the utility of robot i's frontier based on $\widehat{\mathcal{C}_j^f}$. Figure 6 represents such a scenario.

Thus, using the system to retrieve inter-robot positions proposed in section IV-A and the utility calculation proposed in equation (3), our approach aims to achieve improved coordination in frontier-based exploration with minimum information exchange between robots in a team.

V. Experimental Results

A. Testbed and Hardware

We validate our proposed algorithm in simulation as well as hardware. We compare our method against the baseline frontier-based exploration algorithm [12] in which relative locations are not shared between robots. In hardware, we use two Turtlebot3 ground robots equipped with multiple onboard sensors in order to collect data for mapping as well as relative position estimates using wireless signals (Figure 1). Experiments are conducted in a 300 m^2 cluttered environment consisting of bricks, chairs and metal cabinets, amongst others (Figure 7). Experiments in simulation are run with four ground robots. For both hardware and simulation, robots generated a 2D map of the environment using the RTabMap SLAM framework.

B. System validation

We first validate the accuracy of our relative position estimation method for LOS and NLOS. In the cluttered testbed, this method achieves median relative position accuracy of 2.2 meters. Next, we conduct end-to-end exploration experiment for two scenarios. In the first scenario, the two ground robots explore the environment without the ability to obtain relative positions of each other. For the second scenario, one of the robots is now enable with the capability to obtain relative position estimates using wireless signals. Figure 7 shows results comparing the exploration performance for these two scenarios. For the second scenario, we observe that one of robots use the relative position estimates to maintain higher separation between itself and its neighbor as compared to the first scenario indicating lower simultaneous overlap in their individual explored regions.

We also test the scalability of our proposed algorithm in simulation using 4 ground robots. We test three scenarios - i) robots cannot obtain relative position estimates of their neighbors, ii) robots can obtain perfect relative position estimates and iii) robots obtain noisy position estimates of their neighbors (Figure: 8. The noisy position estimates are generated by adding a Gaussian noise $\mathcal{N}(0, 1)$ to the true positions of the robots. By leveraging these noisy estimates, all robots can collectively explore the area faster without relying on any explicit information exchange.

C. Terminating condition

We do not address the problem of exploration termination in this work. Instead, we utilize a centralized, oracle system which requires a complete map of the environment that is collected before running the experiments. The oracle system is running a map merging algorithm, which collects the partial maps of each robot within the team and combines them into a global map. During exploration, the oracle system compares the real-time merged map against the pre-determined map of the environment. Once the system assess that the merged map 90% of the the full environment, it signals robots to terminate exploration. Neither the merged map nor the oracle system is used to communicate any information to the robots during exploration. In future work, we aim to address how robots can collectively decide to end exploration without communicating any information.

VI. Conclusion

This paper shows that sensing over wireless signals can enable the emergence of global coordination behaviors from local onboard algorithms without explicit information exchange. By extracting information directly from the transmitted wireless signals, robots can obtain relative position information without exchanging any additional information such as maps. This enables efficient multi-robot frontier exploration where robots need only their local information to achieve coordination.

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