Communication-Preserving Bids in Market-Based Task Allocation

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***Abstract*— In this paper, we study the effects of impaired communications on the performances of auction-based task allocation in a dynamic surveillance scenario. We propose a novel connectivity term to include in the bid valuation formula, that aims at improving communications in the multi-robot team. We evaluate our method as well as another state-of-the-art method using robot inter-distance to maintain communication, on randomly generated scenarios and on a real-world scenario. We demonstrate that including our connectivity term in the bid valuation formula improves the performances of the auction scheme.**

I. INTRODUCTION

Multi-robot systems (MRSs) are a long active field of research, and their application to surveillance missions have been extensively studied [1], [2]. However, a reliable coordination strategy is needed for an MRS to operate safely and efficiently. An important part of MRS coordination is the Multi-Robot Task Allocation (MRTA) problem, that consists in assigning a set of tasks to the MRS agents [3]. As MRTA is NP-hard, most of the research interested in solving it in real-time scenarios focus on approximate methods.

Among the many methods proposed for MRTA throughout the years, the Market-Based Approaches (MBAs) stand out as some of the most investigated methods. In MBAs, the robots composing the MRS compete for the tasks to be allocated through a market scheme that emulates real-world economic transactions. In particular, a sub-category of MBAs that received much attention are the Auction-Based Approaches (ABAs): the tasks are sold through an auction scheme in which the bidders are the robots [4]. ABAs excel at efficiently and robustly allocating single tasks [5]. However, ABAs require a reliable communication network (CN) for the market scheme to operate properly. For instance, if a robot is disconnected from its teammates, it might be unable to communicate its bids. As a result, an ABA might not allocate any task to this robot. Hence, a degraded CN leads to a surge in inefficiencies. Moreover, the CN typically evolves dynamically, as robots move farther apart. Yet, few works are dedicated to improve the CN in ABAs for MRS.

To address this issue, Sheng et al. proposed an improved ABA that accounts for the CN connectivity by managing the pairwise distance between robots [6]: robots are rewarded for staying close to their teammates. However, this approach does not account for a major element that disturbs communication: physical obstacles may block two robots from communicating regardless of their closeness. In real-world scenarios, such obstacles could severely degrade the CN and create isolated areas. In this paper, we will study a surveillance scenario taking place in the environment displayed in Fig. 1. In this environment, buildings can prevent teammates that are very close, in terms of distance, from communicating. To address this issue in the context of auction-based approaches, we introduce a pricing method that aims at preserving a well-connected CN by considering the CN topology. Our method consists in penalizing allocations that may partition the CN into smaller components connecting disjointed robotic sub-teams, while rewarding allocations that merge CN components into larger components connecting robots through multi-hop communications. We apply this pricing method to a dynamic surveillance mission performed by a team of heterogeneous robots with different moving and sensing capabilities. During the mission, the requirements for surveying some positions evolve dynamically.

Fig. 1. Real-world surveillance scenario. The graph's nodes must be visited by the robots, but require specific sensors. Robots can navigate on the graph's edges. Buildings on the top, left and bottom of the area may block messages.

After a review of the relevant literature, we will explicit the mission that we study and describe the ABA scheme that we use. We then present the bid valuation processes, including the evaluation of our communication-preserving term. Next, we detail our experiments and discuss our experimental results. We conclude our paper by summarizing our main results and proposing directions for future research.

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II. RELATED WORK

The use of MBAs to solve MRTA is a long-studied issue [5], and many improvements to ABAs were introduced to adapt them to more sophisticated requirements that arise in multi-robot surveillance missions: allocating complex tasks using task tree decomposition [7], managing robots joining or leaving the team [8], re-auctioning tasks to robots with lengthy patrol paths to improve a minimax criterion [9], or including a monitoring agent that redistributes tasks of under-performing robots [10].

However, ABAs depend heavily on reliable communications, as the quality of the obtained allocations depends greatly on the loss rate of bid messages. In general, the performances achieved by ABAs decrease as the CN becomes less reliable [11]. Otte et al. [12] conduced a comparative study including many ABAs variants, in a context of degraded communications. The authors showed that all variants perform worst as the message loss probability increased. When the mission objective is to minimize the robots path length on a randomly generated map, the numerical experiments of [12] produced mixed results, as no ABA variant was better than the others across the whole spectrum of message loss probabilities. It is clear that unreliable communications are very detrimental to the quality of the MRTA solutions produced by ABAs, which motivates works aiming at developing and assessing strategies that account for communications when solving MRTA.

To address these issues, many authors have focused on improving the communication protocols among teammates. Ferri et al. [13] proposed a method to reduce communication requirements using a Single-Item Auction (SIA) scheme. Auctioneers only send the announcement messages to the bidders with which they immediately share a communication link in the network. The method proposed in [14], built upon an SIA scheme, allows for proxy agents to gather and filter bids from neighbor agents. Mezei et al. [15] allowed robots receiving an announcement to decide whether they must relay it to subsequent teammates in the network based on an estimation of their bids. Bai et al. [16] used an information consensus procedure to merge the local data of neighboring robots before carrying auction rounds. A score that accounts for the availability of robots has been introduced in [17]; this score depends on the number of task announcements received by a robot: robots with a bad availability score do not engage in further auctions. However, these approaches decrease the communication requirements, but does not improve the ability of robots to share information.

An alternative to ensure a stable CN would be to design a bid valuation formula that accounts for the network's quality, and encourages robots to favor tasks that would maintain a well connected CN. To the extend of our knowledge, the only work proposing such a communication-related bid formulation is the work by Sheng et al. [6]. In their study, the authors defined a measure called the nearness measure, whose purpose is to evaluate the proximity of a robot to its neighbors. More precisely, robots receive rewards that increase when the distances between them and their teammates decrease, multiplied by a factor that decreases for each subsequent neighbor after the nearest. This allows for robots to spread evenly on the map. This measure is used in the bid formula to try to maintain a connected CN during the task allocation process. Simulation experiments showed that it improved the quality of the produced solutions [6]. However, this method takes the distance between robots as the metric for communication quality, which does not hold when obstacles prevent communications, as discussed in the introduction.

In this paper, we then propose to integrate in the bid formula a new communication-preserving term based on the connectivity of the CN, and in particular on the number of robots in the connected components of the CN, rather than on the distance between robots. We then evaluate and discuss the interest of this new term in a real-world scenario including obstacles that may disrupt communications, preventing neighbor robots from communicating even if they are very close.

III. PROBLEM FORMULATION

A. Surveillance Scenario

In this paper, we consider an area surveillance mission performed by a team of robots. Robots are able to communicate via a multi-hop CN. The mission takes place on a known area represented by a graph $\mathcal{G} = \{\mathcal{W}, \mathcal{E}\}$. Robots must survey the waypoints $\mathcal{W}$ as often as possible and are only allowed to move through the edges $\mathcal{E}$ of the graph. We consider the instantaneous idleness of the waypoints, defined by Equation (1), as the metric to determine the effectiveness of the proposed algorithms,

$$\mathrm{I}_w(t) = t - t_{last}^w \tag{1}$$

where $t \in \mathbb{R}_+$ is the current time, and $t_{last}^w \leq t$ is the last visit date of waypoint w. We denote by $\mathbf{t}_{last}$ the vector of last visit times $t_{last}^w, w \in \mathcal{W}$. The mission's objective is to minimize the maximum idleness among all waypoints during the whole mission, as described by Equation (2). This objective ensures that any allocation that left a waypoint without surveillance is disincentivized. Such modeling have been long used in multi-robot surveillance missions [18], [19], [20].

$$\min \max_{w \in \mathcal{W}} \mathrm{I}_w(t), \quad \forall t \in [0, t_e] \tag{2}$$

with t_e the ending date of the mission. To solve this problem, we use a team of robots denoted $\mathcal{R}$. Each robot $r \in \mathcal{R}$ is described by its type $T \in \mathcal{T}$. Robots of the same type have identical moving speed v_T and communication range c_T. They are also equipped with the same set of sensors $\mathcal{S}_T$. Each waypoint $w \in \mathcal{W}$ requires a specific set of sensors to be surveyed, that we denote $S_w \subset \mathcal{S}$. The minimization of the maximum idleness described in Equation (2) is constrained by the ability of different robot types to survey each waypoint. Robots that are not equipped with at least one relevant sensor for a given waypoint, i.e. $S_T \cap S_w = \emptyset$, are not able to survey it. We also assume in this paper that robots are able to determine their position exactly.

ABAs are distributed decision making algorithms. Therefore, robots need to share information with their teammates through a multi-hop network, in order to build a local knowledge of their environment and of their teammates' behavior. In ABAs, robots must share the auction announcements and bids among as many robots as possible to allow the auction round to result in the most efficient feasible allocation [12]. In the multi-robot patrol scenario, the allocated tasks, and the latest visit dates of waypoints are also essential to compute relevant auction bids [20]. For these reasons, we want to ensure that the communication network that connects the robots is highly connected.

B. Dynamic events

In real-world environments, robots encounter unexpected events while executing their tasks. Such events are unpredictable and cannot be accounted for when solving the MRTA problem. In particular, we modeled dynamic events representing real-world situations that alter the sensors needed to survey a waypoint. For instance, a change in lighting conditions may prevent standard visual cameras to survey a waypoint, while night vision cameras will still be able to do so. Also, in the presence of smoke, that may appear during the mission, a specific sensor, such as a thermal camera, is needed to gather data.

A dynamic event is then characterized by the triplet $(w \in \mathcal{W},\ t > 0,\ \mathbf{s}^- \in \mathcal{S}_w)$. The location of the event is given by w, and its date by t, while $\mathbf{s}^-$ represents a set of sensors unable to survey w. In other words, this means that at time t, the list of sensors able to survey w will be updated such that $\mathcal{S}_w \leftarrow \mathcal{S}_w \setminus \mathbf{s}^-$. We consider that the robots are only able to detect these events when trying to survey the concerned waypoint.

IV. AUCTION PROTOCOL

To solve the problem described in Section III-A, we use a Sequential Single-Item Auction (SSIA) scheme [21]. SSIAs are a simple scheme to consider task synergies in an ABA. In SSIA, robots auction tasks one after the other, in subsequent auction rounds. Tasks are auctioned one by one, and robots send their bids one at a time, considering their current plan to value the auctioned task. The auctioneer closes a round after waiting for bids for a fixed amount of time, in order to account for unavailable communications.

In the following, we denote by L_r the list of items to auction of robot r, and by $exec_r$ its list of tasks to execute. To ensure that tasks are reallocated, robots start an auction for each waypoint that they survey successfully. More precisely, when a robot r reaches a waypoint $w \in exec_r$, there are two possible outcomes. If r is equipped with one of the sensors required to survey the waypoint, i.e. $S_T \cap S_w \neq \emptyset$ with T the type of r, then the waypoint is considered as surveyed. In consequence, its idleness is reset to 0, it is removed from $exec_r$, and inserted at the end of L_r. Otherwise, if the robot does not have one of the required sensors for w, the idleness of w if not reset, it is removed from $exec_r$ and inserted at the end of L_r. The robot updates its local knowledge of S_w, and will not bid for this waypoint in future auction rounds. It also broadcasts this information so that its teammates can do the same.

At each auction round, one of the robots with tasks to sell (i.e. $L_r \neq \emptyset$) takes on the auctioneer role, which means that it is in charge of the announcement of the auction: this robot sends task specifications to as many teammates as possible. The auctioneer gathers its teammates' bids, and evaluates them to determine which teammates will receive the task. The teammate receiving the task adds it to its execution set $exec_r$.

The bid valuation function is one of the most important elements of an ABA. It determines the winner of each auction round. In this section, we present two terms proposed in the state-of-the-art to estimate waypoints idleness and the CN quality through a nearness measure. We then present the novel term we propose to estimate the CN quality through a computation of its connected components.

A. Idleness term adapted from Yan and Zhang (2016) [20]

When robot r has to bid on waypoint w, the term proposed in [20] estimates the idleness of w when r will survey it. To do so, this term compares the instantaneous idleness of w (as known by r) with the travel time needed by r to reach waypoint w. We adapted the term proposed in [20] to our SSIA protocol, resulting in the formula given in Equation (3),

$$J_r(t, w) = 1 + \frac{t - \mathbf{t}^r_{last}(w)}{d(r, w)/v_T} \tag{3}$$

where $t \in \mathbb{R}_+$ is the time at which the computation occurs, $\mathbf{t}^r_{last}(w) \leq t$ is the last visit date of waypoint w, $T \in \mathcal{T}$ is the type of robot r, and $d(r, w) \in \mathbb{R}_+$ is the length of the shortest path from the position of r's last target, to w. However, Equation (3) gives much higher values than the other terms described further in Equations (5) and (6), making them irrelevant. Therefore, we must normalize J_r between 0 and 1 so that its values are consistent with the other terms used in our bid formula, resulting in the term given in Equation (4),

$$I_r(t, w) = \frac{J_r(t, w)}{1 + J_r(t, w)}. \tag{4}$$

B. Nearness measure from Sheng et al. (2006) [6]

In this paragraph, we describe the nearness measure as defined in [6]. The nearness measure is given by Equation (5),

$$S_r(t, w, \mathbf{d}) = e^{-\frac{d_1}{c_T}} + \lambda e^{-\frac{d_2}{c_T}} + ... + \lambda^{n_k - 2} e^{-\frac{d_{n_k}}{c_T}} \tag{5}$$

where $\mathbf{d} = \{d_1, ..., d_{n_k}\}$ denotes the pairwise distances between robot r and the robots it is able to communicate with through multi-hop communications, sorted in increasing order. λ is a factor smaller than 1, such that each subsequent robot after the nearest neighbor is valued exponentially less than its predecessor. This ensures that robots are not rewarded for staying in very tight groups, and instead spread quite evenly on the map.

C. Term rewarding the network's connectivity

To preserve a highly connected CN, we introduce a communication term $K_r(t, w)$ described in Equation (6),

$$K_r(t, w) = \frac{\left|C\left(\mathcal{N}\left(t + \frac{d(r,w)}{v_r}\right), r\right)\right|}{\left|C\left(\mathcal{N}(t), r\right)\right|} - 1. \tag{6}$$

In this term, $\mathcal{N}(t) = (\mathcal{R}, \mathcal{F})$ is a graph describing the communication network at time t, with $\mathcal{F}$ the pairs of robots able to communicate with each other, and $C(\Gamma, r)$ the connected component of graph Γ that contains robot r. Note that each robot maintains a local version of $\mathcal{N}(t)$, so the computation of $K_r(t, w)$ is done using only r's local knowledge. To keep $\mathcal{N}(t)$ up-to-date, robots may periodically broadcast pings to check with which teammates they can communicate. However, for simplicity, this aspect was handled through a centralized dispatcher that feeds the CN to each robot.

This term is the ratio between the number of robots in the same sub-CN as the bidder robot r at the starting date t of the auction, and an estimation of the number of robots in the same sub-CN as r at the future date $t + \frac{d(r,w)}{v_r}$ when r will reach the auctioned waypoint w. To compute this second number, we must predict the positions of r's teammates in the future, which necessitates an up-to-date local knowledge of teammates' arrival dates. Formally, we define the number of robots in r's sub-CN as the cardinal of the connected component that contains r in the topological representation of the CN. Note that we subtract 1 to the ratio to ensure that $K_r(t, w)$ is negative if allocating w to r would decrease the number of robots in its sub-CN.

D. Aggregated bid formula

In the forthcoming experiments, we will combine the idleness cost I_r with the communication-oriented costs, S_r and K_r, to build the bid valuation formula. More precisely, the main contribution of this paper is to demonstrate the benefits of using K_r together with I_r to build the bid valuation formula, as described in Equation (7a), in order to solve dynamic scenarios through an SSIA scheme. We will compare our approach with a bid valuation consisting of I_r alone, and with a bid valuation consisting of I_r together with S_r, as described in Equation (7b),

$$B_r(t, w) = I_r(t, w) + K_r(t, w), \tag{7a}$$

$$B_r(t, w, \mathbf{d}) = I_r(t, w) + S_r(t, w, \mathbf{d}). \tag{7b}$$

E. Shared Data

In order to compute their bids on the auctioned tasks, the robots need to share data about the current state of the mission. Robots share their local knowledge to the best of their abilities through multi-hop communications, i.e., to every teammate that is in the same sub-CN. First, to evaluate the idleness cost I_r described in Section IV-A, robots have to share their knowledge of the last visit dates for each waypoint w in order to assess the idleness of the waypoints. To do so, each robot $r \in \mathcal{R}$ maintains a local version of $\mathbf{t}_{last}$, denoted $\mathbf{t}^r_{last}$, that is updated when receiving this value from another robot. Robots send an updated version of $\mathbf{t}^r_{last}$ to their teammates after surveying a waypoint. Upon reception of such message, robots update their list of last visit dates by keeping the element-wise minimum of the received list and their local list. In addition to the last visits dates, robots also need to know the expected paths of their teammates, as they are needed to predict the robots' future positions in order to compute the communication costs presented in Sections IV-B and IV-C. The expected path of a robot is modified only when it receives an award after winning an auction. In consequence, sharing this information do not add much to the communication load, as a unique message is necessary per auction round to maintain an up-to-date version of the expected paths among all robots. Note that the maximum size of this message is attained when a single robot is awarded all the waypoints, and therefore the maximum size of the message is $|\mathcal{W}|$.

V. SIMULATION EXPERIMENTS

A. Simulation set up

The goal of the experiments described in this section is to evaluate the impact of accounting for the CN's connectivity using the connectivity term K_r proposed in Section IV-C. We will compare it with existing ABAs that used the idleness term I_r [20] described in Section IV-A and the nearness measure [6] described in Section IV-B. To do so, we made a first set of experiments on randomly generated scenarios in which the environment is structured as a grid. These scenarios consist of 5×5 grid graphs from which we remove 8 randomly selected edges and on which we randomly place from 4 to 8 physical obstacles that will block communications. 50 such scenarios were generated for the simulation experiments described in this Section. Figure 2 shows one of the generated environments. Note that the area of the real-world missions is much smaller than the area of the grid graphs.

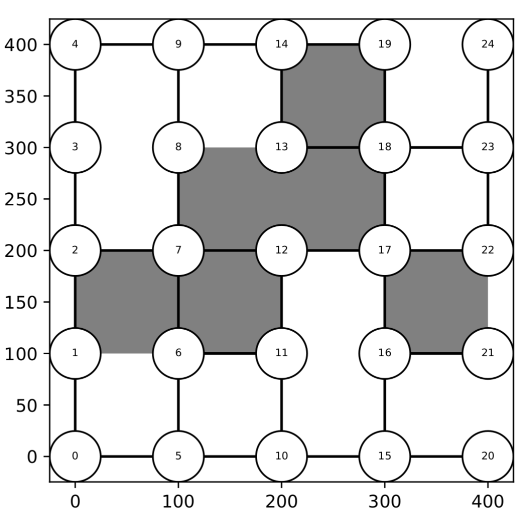


Fig. 2. Randomly generated patrolling scenario. The cells of the grid that are filled in grey represent obstacles that block communication.

Secondly, we used the realistic surveillance scenario whose graph is given in Fig. 1, with a team of five robots.

We evaluated 3 different methods: a simple SSIA scheme using only the idleness term (denoted $B = I$ in the results), an SSIA scheme using Sheng's nearness measure (denoted $B = I + S$), and finally the SSIA scheme containing our contribution, i.e. our CN's connectivity term to improve communications in the MRS (denoted $B = I + K$). To determine the performance of these approaches, we measured the evolution of the maximum idleness among all waypoints. The objective of each method would then be to minimize this maximum idleness.

We set up dynamic events to ensure that the scenario is dynamic, as described in Section III-B. Events are randomly generated such that in average, half the waypoints will require a night vision camera, and a fourth will require a thermal camera. These events have an occurrence date distributed from $t = 0$ seconds to $t = 300$ seconds, and each run lasts 1800 seconds so that the MRTA process has time to converge back to a stable solution. Also, this allows us to examine the impacts of the dynamics events on the idleness of the waypoints. The robot's communication range was set to $c_T = 250$ for all robot types.

In our simulations, the ability for a pair of robots to communicate depends on their communication range, and on physical obstacles that may disrupt communications. In particular, we consider that a pair of robots that does not have a line of sight are not able to communicate. In the randomly generated grid instances, physical obstacles are placed randomly on the grid (see Fig. 2). In our real-world scenario, physical obstacles correspond to buildings as shown on the map of Fig. 1, for instance in the top left corner. Once this random selection is done, we keep the same pairs for the three SSIA variants, ensuring that the methods are evaluated on the same configurations.

Figure 3 shows the evolution of the maximum idleness of waypoints, averaged over 50 runs for each SSIA variant. The 99% confidence intervals of these averages are plotted around the main curves.

B. Results

The results for randomly generated instances represented on Fig. 3a indicate that our approach (blue line) allows for a smoother handling of dynamic events when compared with the two other approaches, as it yields consistently lower values for the maximum idleness. The approach using the nearness measure (red line) is largely dominated by both our approach and the baseline SSIA (green line). This was expected: as it tries to improve communication without accounting for the obstacles, the nearness measure is ineffective in improving communications. Therefore, it only disrupts the optimization of the idleness without bringing any benefits. After some time, the three approaches converge to stable MRTA solutions with similar maximum idleness values.

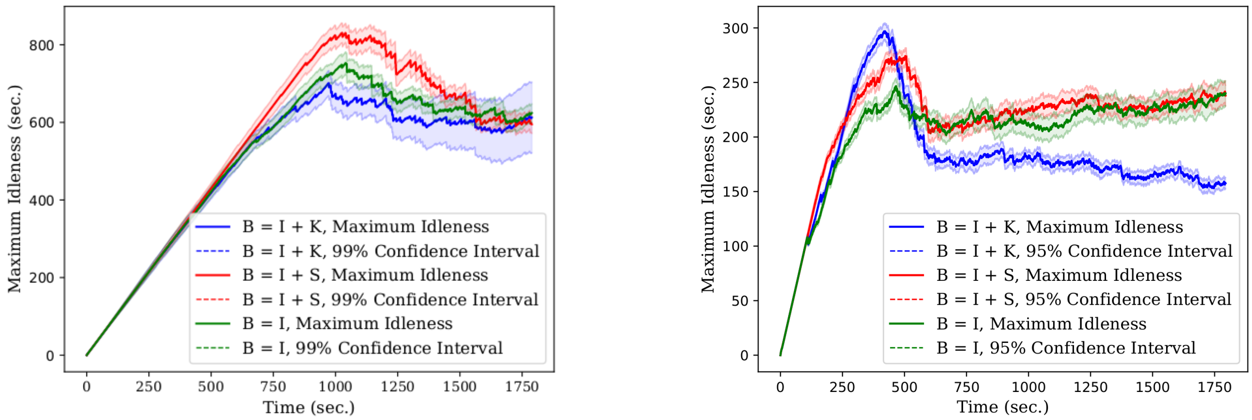
The results from our real-world scenarios of Fig. 3b are quite different. Our approach (blue line) pics higher than the others, but also sooner. This means that it solved many dynamic events at once. In one hand, the height of the pic is explained by quite a few events not being handled before the pic. In the other hand, the earliness of the pic is evidence that all events were handled swiftly. The other approaches handled events more smoothly but also more slowly, as the pic is lower and happens later. In addition, we can see that our approach consistently manages to converge to a much more efficient MRTA solution as time passes. This indicates that the reallocations made by the approach using the nearness measure (in red) and the baseline SSIA (in green) in order to handle the dynamic events, locked them into local minima. Also, the physical obstacles are distributed on the edges of the map, reducing the benefits of the connectivity term with respect to the nearness measure. Obstacles placed on the edges of map do not split the CN into long-lasting disconnected sub-CNs ; robots quickly move around the obstacle and regain access to the full CN. On the contrary, obstacles placed in the middle on the map tend to cause long-term splits in the CN. For instances, on the graph depicted in Figure 2, robots surveying the top left corner of the graph will be disconnected from robots surveying the lower part of the graph. Despite that, our approach was able to outperform the baseline and the approach using the nearness measure by $\approx 34\%$ at the end of the mission.

These results show that using the connectivity cost that we introduced in Section IV-C allows for clear improvements in the maximum idleness yielded by the SSIA scheme. Indeed, our method outperforms the approach using only the idleness term adapted from [20] as well as the approach combining the idleness term and the nearness measure proposed by [6] during most of the duration of the mission. This is true in both the randomly generated grid scenarios, as shown in Figure 3a and the real-world inspired scenarios shown in Figure 3b.

VI. CONCLUSION

In this paper, we studied a dynamic surveillance MRS mission accounting for physical obstacles blocking communications. State of the art methods to solve MRTA for such MRS missions include ABAs, that need a highly connected CN to perform reliably. However, there is no contribution that aims at improving the connectivity of the CN in the existing literature.

To address the issue of maintaining a connected communication network throughout the mission duration, we proposed the network connectivity term, designed to reward allocations that improve the connectivity of the CN. We considered two types of scenarios: randomly generated grids and real-world inspired scenarios. In both scenarios types, a number of dynamic events were randomly generated, causing most of the waypoints to require a specific sensor to be surveyed. To handle these dynamic events, robots had to re-allocate their tasks through an SSIA scheme. However, their communication capabilities were limited by their communication range, and by physical obstacles that may block messages. We produced simulation experiments to compare SSIA schemes using our network connectivity term with similar schemes



(a) Randomly generated grid instances.

(b) Instances modeling the real-world mission presented in Fig. 1

Fig. 3. Results for the maximum idleness. 50 runs were averaged to obtain each curve. The band around each curve represents the 99% confidence interval of the corresponding mean.

that either do not consider communication at all, or try to improve communication using the nearness measure, that relies on the pairwise distance between robots [6].

The results obtained from these experiments show that monitoring the connectivity of the CN using the network connectivity term that we introduced yields better MRTA solutions, as they produce a lower maximum idleness. Our approach allows for a swift and efficient handling of dynamic events in the grid scenarios, and converges to much more efficient allocations in the real-world inspired scenarios.

In future work, it would be interesting to evaluate these methods on a wider range of parameters. Such parameters could include robots' communication ranges, density of physical obstacles in the mission's environment, and proportion of nodes concerned by a dynamic event. We could also explore different graph topologies, such as star-shaped graphs. It would also be useful to define new metrics, in addition to the maximum idleness, that account for the robustness of the approach. Finally, it would be interesting to compare the performances of auction-based approaches with some decentralized optimization-based approaches.

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