Connectivity-Aware Planning of Search and Rescue Missions

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***Abstract*—In this paper, we deal with the problem of planning the activities of a team of mobile agents to maximize the performance of a mission, and, at the same time, enhancing the communication between them. We propose a novel approach based upon the use of connectivity directives, whose compliance is expected to translate into beneficial conditions for data exchange. Using the approach in the context of search and rescue missions, we conform a connectivity-aware planning, in which directives take the form of spatial relations among groups of agents. In the planning process, we let the user to establish the desired trade-off between connectivity provisioning and mission performance, which in turn results in mission plans that exhibit a balance between these two aspects. The evaluation indicates that, by using the connectivity-aware planning, we can greatly increase the quality of the communication at a very low expense of mission performance.**

I. Introduction

Current search and rescue (SAR) missions feature the combined use of technologies (e.g., robots) and human and animal agents (e.g., dogs) each providing different capabilities and expertise. In the resulting heterogeneous teams some agents are more capable to perform certain tasks than others, leading to the complex problem of assigning roles and responsibilities to the agents during the mission. Therefore, *mission planning* for heterogeneous teams consists in jointly deciding and coordinating the activities of the agents in order to perform the tasks as efficiently as possible, exploiting at the best their individual capabilities and their mutual synergies.

The management of SAR missions is typically carried out at the so-called mission *command center*, the physical place that posses the means to receive, collect, process, and analyze all the information regarding the mission. It also dispatches the mission plans to the agents in the field and gathers the necessary personal to exert command and control of all the activities concerning the mission. Under this operation mode, a frequent, bidirectional data exchange between the command center and the agents deployed in the field is crucial for the proper functioning of the SAR team.

Unfortunately, it is a common situation that a networking infrastructure is either missing or is only partially operational in the area where the SAR team is operating in. For instance, this is often the case for SAR in the wilderness (WiSAR). In these cases different solutions may be employed to provide support for communication. In this work we consider the most general approach to this problem, assuming that communication in the field is supported by a wireless ad hoc network dynamically built by the team. In these networks, data can travel across the network in a multi-hop way, with the possibility of communication between two nodes being directly related to their physical separation distance.

Given the criticality of data exchange between the agents and the command center, as well as among the agents themselves, the mission planner faces a problem with two potentially conflicting objectives. First, since mission-related tasks have to be carried out at well specified locations in the environment (e.g., search along a path in the woods), the planner has to specify actions and trajectories of the agents that would jointly optimize the search performance. Secondly, in order to enable the formation of local network topologies that permit the required flows of information, the planner also needs to address the notion of spatial proximity among the agents, aiming to support multi-hop wireless communication. In practice, supporting wireless networking imposes constraints to the way the agents can move, constraining in turn how SAR-specific actions are performed.

The problem of providing ad hoc communication in a team of agents executing a mission has been addressed in several different domains such as multi-robot exploration [1], [2], [3], [4], path planning and navigation [5], [6], [7], [8], [9], [10], surveillance [11], [12], and pursuit and evasion [13]. A common way to address the problem is through the dedicated use of a group of agents as *communication providers*, whose only objective is to enable data communication. These approaches include building and maintaining a communication infrastructure [14], [15], [16]. However, since the number of agents is limited, permanently using a fraction of them to keep an infrastructure intrinsically limits the *spatial range* of the mission. One way to extend this range is, for instance, through the use of *data mules*, that is agents that constantly move back and forth between the base station and the rest of the team [17], [2]. The common implication of all these approaches is that some members of the team will be given the exclusive task of supporting communication, thus sacrificing for the sake of networking their potential contribution to the specific mission (e.g., in terms of performing search). From the point of view of planning, this way of proceeding considers separately the problems of mission planning and provisioning of communication.

In another set of works the agents simultaneously play the role of communication providers and task executors. To this end, the provisioning of communication and planning of SAR activities are usually considered as integrated issues. Most of the approaches in this sense enforce the *continual satisfaction of hard communication constraints* (e.g., in terms of proximity among the agents), that significantly restrict the ways that the mission can be accomplished. Examples of these include establishing permanent communication paths between a base station and a group of agents [11], [5], [18], [19], [8], [1], ensuring global connectivity among the agents [3], [20], [10], [4], setting up direct communication links between specific pair of agents [21], to a minimum number of agents [22], or between one particular agent and the rest of the team [13].

Enforcing continual connectivity is justified in communication-critical scenarios where lack of communication can result in the failure of the mission (e.g., tele-operated robots, real-time image streaming). Instead, in other scenarios it can be reasonable to relax the strong requirement of permanent connectivity, allowing intermittent forms of network connectivity. Along this line, some works have adopted flexible connectivity goals such as *periodic connectivity* [7], in which the network can be disconnected during bounded, time periods, regaining connectivity at fixed intervals, and *recurrent connectivity* [12], in which the system must regularly become connected and remain in that state for a minimum amount of time. In this way, mission requirements for communication can still be satisfied, while, at the same time, it is possible to enable the system to reach mission performance levels that otherwise would be impossible to achieve under strong connectivity constraints. However, in these works, it is not clear for the user what is the performance gain (if any) due to the relaxed connectivity requirements. Moreover, it is not possible to explicitly control the *trade-off* between connectivity provisioning and mission performance.

Unlike prior efforts, we propose a novel way of providing communication to a team of agents that does not enforce particular network topologies, restrict the physical locations of the agents, or consider networking and search as separate problems. Instead, it promotes the occurrence of spatial relations among the agents, which are aimed to favor any form of communication (e.g., multi-hop, opportunistic), through the direct inclusion of connectivity directives inside the planning process. We let the user to establish the desired trade-off between communication provisioning and mission performance, which in turn results in mission plans that exhibit a balance between those two aspects.

More specifically, the work on network connectivity presented in this paper extends previous work [23], [24] in which we formulated the SAR mission planning as an optimization problem and we focused on SAR in large wilderness areas (WiSAR). The objective was to jointly define, for all agents in a heterogeneous SAR team, the search trajectories and the activity scheduling that maximize the coverage of the area. Trajectories consist of sequences of sectors, while activity scheduling provides the amount of time that each agent should spend performing the search task within each sector composing its trajectory. We assume that the performance of an agent is characterized by a linear *spatial coverage rate* which relates the local terrain characteristics and the agent skills to the amount of area covered over time. Under this condition, team mission planning can be formulated as a mixed-integer linear programming (MILP) optimization problem.

In summary, our contributions include the following. (i) A novel methodology to enhance communication in missions involving a team of networked agents executing spatially distributed tasks that promotes communication through the specification of *connectivity directives* or guidelines, and also allows to establish the desired trade-off between communication and mission performance. (ii) The application of the proposed framework in the context of search and rescue missions, resulting in a *connectivity-aware mission planning*. (iii) The evaluation of the connectivity-aware planning using sets of directives inspired in typical communication strategies used in SAR missions.

The rest of the paper is organized as follows. In section II we provide an overview of the SAR planning problem, and discuss the main aspects of the modeling approach. Next, in section III we formalize the connectivity-aware mission planning as an MILP optimization problem. In section IV, we present the evaluation of the proposed framework using network simulations in which the mission plans ignoring the communication issues are compared against plans obtained using the connectivity-aware approach. Finally, we draw conclusions and discuss future work in section V.

II. System Model

In this section we present the way we modeled the reference WiSAR scenario, which is directly derived from our previous work [24]. First, in order to effectively evaluate the status of the search, assign properties to the local environment, and measure the performance of mission plans, the search area of a WiSAR mission is discretized into a set of squared *environment cells*, representing the smallest spatial elements. In the following, without losing generality, a uniform cell grid decomposition is considered, and the cells' set is indicated by $\mathcal{C}$.

Environment cells serve as a means of evaluating mission status in terms of coverage. The *coverage map* $C_m : \mathcal{C} \mapsto [0, 1]$, relates cells to numerical values representing the amount of coverage required, or, in other words, the *residual need of exploration* of each cell. For instance, for $c \in \mathcal{C}$, a value $C_m(c) = 1$ indicates that the cell still *requires* a full exploration (i.e., full coverage). On the other hand, $C_m(c) = 0$ indicates no interest in exploring the cell, either because it has been already explored or because the user is certain that the target is not located there (e.g., because of prior knowledge).

Based on the above cell definitions, the area is further partitioned in *sectors* for the purpose of efficient search. In fact, it should be noted that performing mission planning at the resolution of individual environment cells may become both unpractical, given the uncertainties inherent to the WiSAR missions, and computationally unfeasible, if cells are numerous. Therefore, the goal of a sector-based search is to serve as a framework to allocate the effort inside the area, and to enable the searchers to complete alternating objectives in a reasonable time. Defining the sector boundaries requires a careful analysis, and ideally, knowledge of the region. In case of a heterogeneous team, the definition of possible sectors must be done taking into account the agents' capabilities and terrain conditions. Sectors intended to be searched with ground resources (e.g., a wheeled robot) may require different boundaries and sizes than sectors intended to be searched from an aerial point of view (e.g., a flying robot), in order to account for their different characteristics of mobility and sensing. In the following, for sake of simplicity, we assume that the set of sectors is provided as input to the system, more specifically as a list of geographically delimited regions (i.e., polygons on the earth's surface), each of which can be conveniently described as a cluster of contiguous environment cells (i.e., a subset of $\mathcal{C}$).

Once the set of sectors has been defined, then the issue becomes that of allocating the resources inside the sectors and deciding when, from whom, and how much effort each sector will receive. This is accomplished by the specification of *agent plans*, which are defined in terms of *search tasks*: dispatching the agents to sectors with the objective of carrying out exploration activities for a certain amount of time. A *global mission* *plan* consists of sequences of search tasks to be executed one after the other by each one of the agents. Search tasks are represented by $\langle L, t_{start}, t_{end} \rangle$, where $L \subseteq \mathcal{C}$ is a sector, and t_{start} and t_{end} are the starting and ending times of a search task inside sector L. For simplicity, and without losing generality, the whole mission time is discretized into *mission intervals* of equal length Δ_t seconds. That is, Δ_t is the common *time unit* of the starting, ending, and duration of all search tasks.

In order to compute efficient joint mission plans, the planner must explicitly take into account the fact that different agents may show different levels of performance accomplishing the same task in the same portion of the environment due to their heterogeneous skills, as well as the effect of local conditions (e.g., unmanned aerial vehicles operating in densely vegetated areas may not be able to effectively detect targets on the ground using vision sensors, humans walking up a steep hill might move at a considerably slow pace). One way to accomplish this is to extract relevant environment properties from spatial data provided by *geographical information systems* (GIS) and to define procedures for estimating the *expected search performance* (also termed *search efficacy* in the following), for each single agent and for each different portion of the environment [23], as shown in Fig. 1. In the following, we denote the set of agents

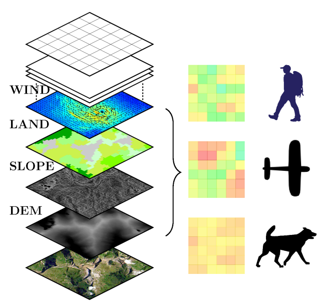


Fig. 1: Estimation of agents' search efficacy using GIS.

as $\mathcal{A}$ and we assume that the search efficacy is specified by the *coverage rate*, $\hat{\varphi}_k$. When an agent $k \in \mathcal{A}$ performs an exploration task inside cell $c \in \mathcal{C}$ for t seconds, it provides the $100 \cdot \hat{\varphi}_k(c)t$ percent of its coverage.

Since mission planning is done in terms of assignments of sectors to agents, the expected search performance $\varphi_k(L, c)$ serves as a tool to *estimate* the coverage that will be done inside cell c by the activities of agent k inside sector L for one time unit (i.e., Δ_t seconds). In other words, φ_k provides an estimation of the way the effort of k will be split among cells composing a sector. For simplicity, and without losing generality, we assume that the time assigned to a sector is uniformly distributed among all its composing cells. For $c \in \mathcal{C}$, $k \in \mathcal{A}$, and $L \in \Gamma_k$:

$$\varphi_k(L, c) = \begin{cases} \hat{\varphi}_k\,(c) \left(\dfrac{\Delta_t}{|L|} \right) & \text{if } c \in L \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where Γ_k is the set of sectors assignable to agent $k \in \mathcal{A}$.

Fig. 2 presents an example of sector decomposition, together with a definition of φ. In the figure, the area has been decomposed into 16 cells, as shown in the square grid at the top. Two different sector layouts are defined, one for a human rescuer and the other for an aerial vehicle. The layout on the right defines 16 sectors of same size as cells, thus a one-to-one

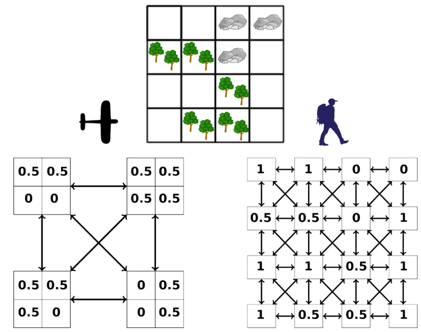


Fig. 2: Sector layouts for two agents.

correspondence between cells and sectors. On the left, 4 sectors composed by 4 cells each are defined. The numbers inside the figure indicate the estimated search performance $\varphi_k(L, c)$ for agents corresponding to each one of the layouts.

III. Mission Planning as Optimization Problem

We formulate the mission planning as an optimization problem. The objective is to jointly define, for all agents in the SAR team, search trajectories and activity scheduling seeking for the maximal efficiency of the mission performance.

We start by defining for each agent $k \in \mathcal{A}$, a *traversability graph* $G_k = (\Gamma_k, E_k)$ where E_k contains an edge (i, j) if a task at sector j can be scheduled right after a task at sector i. We assume that the traveling times between tasks are negligible, and can be implicitly taken into account within the time allocated to perform the tasks. Let $\Gamma_k^0 \subseteq \Gamma_k$ be the sectors which are accessible from the agent's initial position, and Γ denotes the set of all sectors to which agents can be assigned, $\Gamma = \bigcup_k \Gamma_k$.

Given a limited time budget T (e.g., mission's time span), a plan for an agent k specifies an elementary path p_k in G_k (i.e., a sequence of sectors). The path must start with a sector belonging to Γ_k^0, and does not necessarily include all sectors Γ_k due to the time constraints. We denote the set of sectors *visited* or included in tasks assigned to agent k's plan as $v(p_k)$. The amount of time (expressed in Δ_t units) assigned to each sector in the plan is represented by the *schedule function* $s_k : \Gamma_k \mapsto \mathbb{N}$, with $s_k(v) > 0$ if $v \in v(p_k)$ and $s_k = 0$ otherwise.

The sum of the schedule of each agent must be equal to the time budget T, that is $\sum_v s_k(v) = T$. A solution to the mission planning problem consists of paths p_k and schedules s_k for all agents k composing the team of rescuers $\mathcal{A}$, and it is denoted by $\mathcal{P} = \{< p_k, s_k > | k \in \mathcal{A}\}$.

The quality of a mission plan $\mathcal{P}$ in terms of *area coverage* is determined by the effect of agents activities on the current status of the coverage map. Given that C_m^0 indicates the initial coverage map, the *coverage* of a mission plan $\mathcal{P}$ is defined as:

$$\Phi(\mathcal{P}) = \sum_{c \in \mathcal{C}} \Phi_c \tag{2}$$

where,

$$\Phi_c = \min \left(C_m^0(c), \sum_{k \in \mathcal{A}} \sum_{v \in v(p_k)} \varphi_k(v, c) s_k(v) \right). \tag{3}$$

In other words, the effect of plan $\mathcal{P}$ on the coverage of a cell $c \in \mathcal{C}$ (i.e., Φ_c) ranges from 0 (i.e., no quantifiable effect) up to C_m^0 (i.e., completely fulfilling the initial coverage requirements

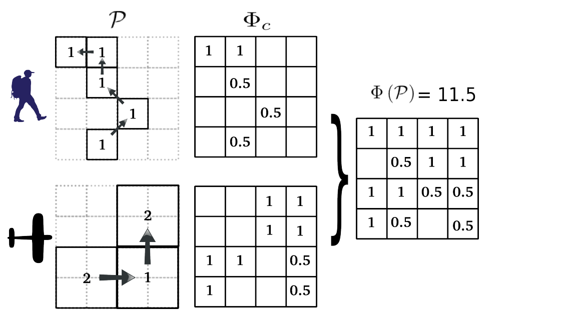


Fig. 3: Example of mission plan for a team of two agents, one human rescuer and one aerial vehicle.

$$\text{maximize} \sum_{c \in \mathcal{C}} \Phi_c \tag{4}$$

subject to

$$\sum_{(0,j) \in E_k} x_{0jk} = 1 \quad \forall k \in \mathcal{A} \tag{5}$$

$$\sum_{(j,0) \in E_k} x_{i0k} = 1 \quad \forall k \in \mathcal{A} \tag{6}$$

$$\sum_{(i,j) \in E_k} x_{ijk} = \sum_{(j,i) \in E} x_{jik} = y_{jk} \quad \forall k \in \mathcal{A},\ i,\ j \in \Gamma_k \tag{7}$$

$$t_{ik} + w_{ik} - t_{jk} \leq (1 - x_{ijk})\, T\ \forall k \in \mathcal{A},\ (i,j) \in E_k,\ i,j \neq 0 \tag{8}$$

$$y_{ik} \leq t_{ik}, w_{ik} \leq T y_{ik} \quad \forall k \in \mathcal{A},\ i \in \Gamma_k \tag{9}$$

$$\Phi_c \leq \sum_{k \in \mathcal{A}} \sum_{i \in \Gamma_k} \varphi_k(i,c) w_{ik} \quad \forall c \in \mathcal{C} \tag{10}$$

$$0 \leq \Phi_c \leq C_m^0(c) \quad \forall c \in \mathcal{C} \tag{11}$$

$$t_{ik},\ w_{ik} \in \mathbb{N} \quad \forall k \in \mathcal{A}, i \in \Gamma_k \tag{12}$$

$$x_{ijk},\ y_{jk} \in \{0,1\} \quad \forall k \in \mathcal{A},\ i,j \in \Gamma_k \tag{13}$$

Fig. 4: MILP formulation of the mission planning.

of c). The minimization in (3) establishes these bounds. Note that the coverage of a cell can be affected by the tasks of any number of agents. Therefore, it is necessary to jointly consider all agents' plans when computing Φ_c, as done in (3).

Consider again the example shown in Fig. 2. Let us assume that the possible transitions between sectors are those indicated in the figure (i.e., moving through contiguous sectors). An example of a feasible mission plan for $\mathcal{A}$ is illustrated in Fig. 3.

A. *Mixed-integer linear formulation*

Making use of the notation introduced above, the mission planning can be formalized as an MILP problem. In order to simplify the description of the model, we will consider a dummy vertex (represented by 0) as the starting and ending points of agents' paths p_k. To this end, graphs G_k are extended by adding arcs from 0 to each of the sectors in Γ_k^0 and from all sectors Γ_k to the dummy 0.

The *decision variables* of the model are the following:

x_{ijk}: binary, equals 1 if agent k traverses arc $(i,j) \in E_k$;
y_{ik}: binary, equals 1 if agent k *visits* sector $i \in \Gamma_k$;
Φ_c: total coverage provided to cell $c \in \mathcal{C}$ by all agents;
t_{ik}: arrival time of agent k at location $i \in \Gamma_k$;
w_{ik}: time spent by agent k at sector $i \in \Gamma_k$.

The MILP formulation for SAR planning is presented in Fig. 4. Constraints (5-6) ensure that paths start and end at the dummy vertex 0. Path continuity is guaranteed by constraints (7). Constraints (8) eliminate subtours and, together with (9), they define the bounds of variables t and w. The coverage of each cell, as explained in (3) is bounded by constraints (10-11). Finally, constraints (12-13) set the integer and binary requirements on the model variables. This formulation represents the core of the model which can be used to maximize the utility of joint agent plans (i.e., maximize coverage). Additional details can be found in [24].

B. *Connectivity-Aware Mission Planning*

In order to introduce the use of connectivity directives in the mission planning, we extend the previous model with two types of directives. The first, called *instant connectivity directives*, refer to spatial relations between sets of agents at specific points in time. The second, *recurrent connectivity directives*, refer to conditions over time periods.

Let ψ_{r} be the transmission range of the network. Let ψ_{ij} be the estimated distance, in meters, between sectors $i,\ j \in \Gamma$. Since sectors are regions within the area of interest, the value of ψ_{ij} may represent, for instance, the distance between their centroids, or some other notion of *expected* distance between agents carrying on activities inside these sectors. In this work, we adopt the former choice.

Let $\mathcal{A}', \mathcal{A}'' \subset \mathcal{A}$ be two disjoint subsets of agents, and $1 \leq \tau \leq T$ a point in time, hereafter also called a *control point*. We represent an *instant connectivity directive* by a tuple $(\mathcal{A}', \mathcal{A}'', \tau)$, meaning that, at control point τ, *all* agents in $\mathcal{A}'$ must lie within the transmission range ψ_{r} of *at least one* agent in $\mathcal{A}''$. We further denote I as the set of the predefined instant connectivity directives for the current model.

To allow the inclusion of instant connectivity directives inside the MILP model, we define the following time-indexed variables, referring to status values at control point τ:

y_{ik}^{τ}: binary, equals 1 if agent k is at sector $i \in \Gamma_k$;
d_{kl}^{τ}: distance between agents k and l.

To define the variables y_{ik}^{τ}, we need to enforce the condition:

$$y_{ik}^{\tau} = 1 \Leftrightarrow (t_{ik} \leq \tau \leq t_{ik} + w_{ik} - 1)\,; \tag{14}$$

which is achieved with the following linear constraints:

$$(T - \tau)\, y_{ik}^{\tau} + t_{ik} \leq T \quad \forall k \in \mathcal{A}, i \in \Gamma_k, \tau \tag{15}$$

$$(\tau + T + 1)\, y_{ik}^{\tau} - T \leq t_{ik} + w_{ik} \quad \forall k \in \mathcal{A}, i \in \Gamma_k, \tau \tag{16}$$

$$\sum_{i \in \Gamma_k} y_{ik}^{\tau} = 1 \quad \forall k \in \mathcal{A}, \tau \tag{17}$$

$$\sum_{\tau} y_{ik}^{\tau} \leq T y_{ik} \quad \forall k \in \mathcal{A}, i \in \Gamma_k \tag{18}$$

$$y_{ik}^{\tau} \in \{0,1\} \quad \forall k \in \mathcal{A}, i \in \Gamma_k, \tau. \tag{19}$$

Once variables y_{ik}^{τ} are included in the model, the distance variable is defined by the following constraints:

$$\psi_{ij}\left(y_{ik}^{\tau} + y_{jl}^{\tau}\right) - \psi_{ij} \leq d_{kl}^{\tau} \quad \forall k, l \in \mathcal{A}, i \in \Gamma_k, j \in \Gamma_l, \tau \tag{20}$$

$$0 \leq d_{kl}^{\tau} \quad \forall k, l \in \mathcal{A},\ \tau. \tag{21}$$

Given instant directive $\beta = (\mathcal{A}', \mathcal{A}'', \tau)$, we introduce a binary indication variable n_{β} that takes value 1 if β is not satisfied in the current solution, and 0 otherwise. By definition, β is not satisfied if there exists an agent $k \in \mathcal{A}'$ such that no agent $l \in \mathcal{A}''$ is within the transmission range ψ_{r} at control point τ. In terms of model variables, the following relationship must be enabled:

$$n_\beta = 1 \Leftrightarrow (\exists k \in \mathcal{A}' \mid (\forall l \in \mathcal{A}'' \mid d_{kl}^\tau > \psi_\mathrm{r})) \quad (22)$$
$$\Leftrightarrow \neg (\forall k \in \mathcal{A}' \mid (\exists l \in \mathcal{A}'' \mid d_{kl}^\tau \leq \psi_\mathrm{r}))\,. \quad (23)$$

Let $\Theta_{k\mathcal{A}''}^\tau$ be the minimum distance between the agents in $\mathcal{A}''$ and agent k, then (23) can be stated as follows:

$$n_\beta = 1 \Rightarrow \neg (\forall k \in \mathcal{A}' \mid \Theta_{k\mathcal{A}''}^\tau \leq \psi_\mathrm{r}) \quad (24)$$

which needs to be expressed as a set of linear constraints. At this aim, we first define variables Θ using the following:

$$\Theta_{k\mathcal{A}''}^\tau = d_{kl}^\tau - \hat{\Theta}_{kl\mathcal{A}''}^\tau \quad \forall k \in \mathcal{A}', l \in \mathcal{A}'', \tau \quad (25)$$
$$\hat{\Theta}_{k\mathcal{A}''}^\tau \leq \mathcal{D}\left(1 - \breve{\Theta}_{kl\mathcal{A}''}^\tau\right) \quad \forall k \in \mathcal{A}', l \in \mathcal{A}'', \tau \quad (26)$$
$$1 \leq \sum_{l \in \mathcal{A}''} \breve{\Theta}_{kl\mathcal{A}''}^\tau \quad \forall k \in \mathcal{A}', l \in \mathcal{A}'', \tau \quad (27)$$
$$0 \leq \hat{\Theta}_{k\mathcal{A}''}^\tau, \quad \breve{\Theta}_{kl\mathcal{A}''}^\tau \in \{0,1\} \quad \forall k \in \mathcal{A}', l \in \mathcal{A}'', \tau \quad (28)$$

where $\mathcal{D}$ is a large value (e.g., maximum possible distance between two agents). We make use of two helper variables: $\hat{\Theta}_{kl\mathcal{A}''}^\tau$ and $\breve{\Theta}_{kl\mathcal{A}''}^\tau$, defined by constraints (25) and (26), respectively. $\hat{\Theta}_{kl\mathcal{A}''}^\tau$ is a real, positive valued variable representing the difference between the distance from agent k to agent $l \in \mathcal{A}''$ and the actual minimum distance from k to any agent in $\mathcal{A}''$. $\breve{\Theta}_{kl\mathcal{A}''}^\tau$ is a binary indication variable that takes value 1 if the corresponding $\hat{\Theta}_{kl\mathcal{A}''}^\tau$ is greater than zero, 0 otherwise. Constraints (27) ensure that at least one of the $\breve{\Theta}_{kl\mathcal{A}''}^\tau$ must be 1, which means that $\Theta_{k\mathcal{A}''}^\tau$ must be equal to one of the distances d_{kl}^τ. Since by definition $\hat{\Theta}_{kl\mathcal{A}''}^\tau$ must be greater or equal to zero, then, as a result, $\Theta_{k\mathcal{A}''}^\tau$ will be equal to the minimum distance between k and all agents in $\mathcal{A}''$.

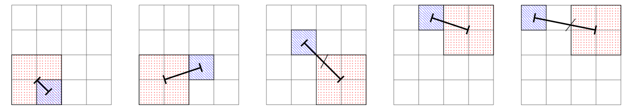
Using the previous definitions, we can then restate (24) in a linear form as:

$$\Theta_{k\mathcal{A}''}^\tau \leq \mathcal{D} n_\beta + \psi_\mathrm{r} \quad \forall \beta \in I, k \in \mathcal{A}' \quad (29)$$
$$n_\beta \in \{0,1\} \quad \forall \beta \in I. \quad (30)$$

Our connectivity-aware planning is further extended with a powerful class of directives termed *recurrent connectivity directives*. These promote the occurrence of an associate set of instant directives at periodic intervals. A recurrent connectivity directive is represented by a tuple $\gamma = (I', \tau', \delta)$, where $I' \subseteq I$ is a selected set of instant directives corresponding to control points within the interval $[\tau', \tau' + \delta]$. A recurrent directive γ is obeyed if *at least* one of the instant directives I' is followed. Similar to instant directives, we introduce a binary indication variable n_γ that takes value 1 if γ is not satisfied in the current solution, and 0 otherwise. We denote the set of recurrent directives by R. Given the previous definition, variables n_γ are included in the model using the following:

$$\sum_{\beta \in I'} n_\beta - |I'| + 1 \leq n_\gamma \quad \forall \gamma \in R \quad (31)$$
$$n_\gamma \in \{0,1\} \quad \forall \gamma \in R. \quad (32)$$

Violations of connectivity directives (either instant or recurrent ones) are reflected in the objective function as *penalty values*. The penalty is proportional to the amount of directives that are not satisfied in a solution. However, since some directives might be more desirable than others (e.g., some of them could be of critical importance), we also include in our framework a *directive weighting function* $\Omega : I \cup R \mapsto \mathbb{R}$, which can be used to indicate the *relative weight* of the violation of each single directive with respect to the others.



(a) $\tau = 1$ (b) $\tau = 2$ (c) $\tau = 3$ (d) $\tau = 4$ (e) $\tau = 5$

Fig. 5: Distances between agents at each time step.

Before stating the inclusion of the penalty values, we first normalize the objective function (4) and refer to it as the *coverage component* (Φ_{cov}):

$$\Phi_{cov} = \frac{\sum_{c \in \mathcal{C}} \Phi_c}{\sum_{c \in \mathcal{C}} C_m^0(c)}. \quad (33)$$

Finally, violations of connectivity directives $\in I \cup R$ in a solution are reflected in the *connectivity component* (Φ_{conn}):

$$\Phi_{conn} = \frac{\sum_{\beta \in I} \Omega(\beta) n_\beta + \sum_{\gamma \in R} \Omega(\gamma) n_\gamma}{\sum_{\beta \in I} \Omega(\beta) + \sum_{\gamma \in R} \Omega(\gamma)}. \quad (34)$$

Note that by definition, $0 \leq \Phi_{cov}, \Phi_{conn} \leq 1$.

The connectivity-aware model is defined as:

$$\text{maximize } (\Phi_{cov} - \lambda \Phi_{conn}) \quad (35)$$
$$\text{subject to}$$
$$(5)\text{–}(13),\ (15)\text{–}(21) \text{ and } (25)\text{–}(34),$$

where λ is a parameter that sets the trade-off between mission coverage and the compliance of connectivity directives.

The definition of the set of directives $I \cup R$, together with the parameters Ω and λ, represent a strategic decision framework, which may involve the analysis of the particular problem instance being considered (e.g., characteristics of the area, composition of the team).

To conclude this section, we present an illustration of the use of connectivity-aware planning. Let us consider again the example of Fig. 3. Assuming that each environment cell has size of $100 \times 100\,\mathrm{m}^2$, the distances between both agents at each time step ($1 \leq \tau \leq 5$) are illustrated in Fig. 5. From Fig. 3, we know that $\Phi_{cov} = \frac{11.5}{16} = 0.72$. Let us assume that we would like to promote instant connectivity directives between both agents, at all time steps, with a transmission range $r = 200$m. That is, $I = \{(\{human\}, \{aerial\}, \tau) \mid 1 \leq \tau \leq 5\}$. In the example, these directives are violated at $\tau = 3$ and $\tau = 5$, when the distances are 212m, and 255m, respectively. Thus, the connectivity component becomes $\Phi_{conn} = \frac{2}{5} = 0.4$. This reduces the *quality* of the proposed solution to $0.72 - 0.4\lambda$, and depending upon the value of the penalty λ, the solution could no longer be optimal. Preference can therefore be given to other feasible solutions which might satisfy more connectivity directives at the expense of only a small reduction in coverage.

IV. Evaluation

In this section we demonstrate the applicability of the developed framework through a series of simulation experiments. In particular, we employ the connectivity-aware planning to enhance the communication between the team of agents and a stationary base station (i.e., the command center). We considered two different set of connectivity directives inspired in strategies typically employed in other works. The first, which we refer to as *RelayChain*, promotes the use of a subset of agents as communication relays, building a chain connected to the base station. The second strategy, called *DataMules*, motivates the use of a subset of agents as data mules, traveling back and forth between the base station and the other agents of the team. In this way data mules can carry the data collected from the agents to the base station. As pointed out in the previous section, the choice of model parameters corresponding to the connectivity-aware planning (i.e., set of directives, Ω, and λ) represents a strategic decision, over a vast number of different possible settings. Therefore, the purpose of this evaluation is not to determine the best setting, but to study the impact of using of the connectivity-aware planning, and compare it against the planning carried out ignoring the communication issues (i.e., network unconstrained case).

To this end, the experimental evaluation consists of three steps. First, we compute mission plans for the network unconstrained case, and for each one of the strategies. Second, we use a custom simulator of agent mobility [24], to obtain fine grained trajectories for all the agents. The simulator receives as input the mission plans, the GIS data of the area (e.g., elevation map, vegetation), and *agent profiles*, that characterize the effect of the terrain over the movement of the agents. The final step makes use of these trajectories to evaluate the data delivery using realistic network simulations.

For the computation of plans we use an off-the-shelf MILP solver, namely CPLEX®. We remark that many other solvers or solution approaches (see, e.g.,[25]) can be used to find feasible or optimal solutions to the MILP problem. However, we will like to emphasize that in this paper we do not intend to compare different solution approaches, but to some extent evaluate the benefits of using of the connectivity-aware planning, independently of the solver used.

To evaluate the network performance, in terms of delivered data at the command center, we employ an opportunistic *delay-tolerant* protocol (DTN) for multi-hop data exchange [26]. The choice of a DTN protocol is motivated by the fact that standard data routing protocols require to set up and maintain data routes, something that is intrinsically difficult to realize in practice when facing high mobility and/or a cluttered environment, which are precisely the conditions that are expected in a SAR scenario. Instead, DTN protocols are able to exploit at most the transient communication links, and to ensure the functioning of the system even with adverse environment conditions that complicate the wireless transmissions [27]. DTN are also particularly useful in applications in which a delay-throughput trade-off is a design choice (i.e., real-time data gathering is not a requirement), such as the scenarios we are considering.

As network simulation environment, we use the ns-3 network simulator [28] with the following configuration. We simulated 802.11b Wi-Fi networks with the transmission rate of 2 Mbps. We used a log-distance propagation loss model with default parameters. The setting of the simulation parameters corresponds to a transmission range of roughly 200 m. During the course of the simulation, nodes follow the trajectories previously generated by the agent mobility simulator. Nodes generate data packets of size 120 kB every 60 seconds. This data generation simulates scenarios in which agents aggregate the sensor data (e.g., GPS positions) and send the information back to the command center. At the network layer, we used the DTN protocol described in [26], as previously mentioned, which is publicly available as an ns-3 module.

A. Communication strategies

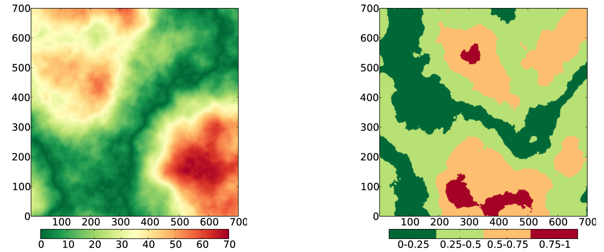
In order to implement the directives, we included the command center as an additional agent a_{com} in the set $\mathcal{A}$. This agent is initially located at the starting position of the team, and stays there during the whole mission.

The *RelayChain* strategy selects a subset of agents ($\mathcal{A}_R \subset \mathcal{A} \setminus \{a_{com}\}$), called *relays*, to conform a chain, connected to the command center. Agents $\mathcal{A}_R$ are enumerated, and denoted as $a_{r,1}, \ldots, a_{r,n}$. Directives are classified into two groups: those that promote the formation of the chain, and those that promote the connectivity between the rest of the team $\mathcal{A} \setminus (\mathcal{A}_R \cup \{a_{com}\})$. The formation of the chain is guided by instant directives $\{(\{a_{r,1}\}, \{a_{com}\}, \tau)\}$, which link the command center to the first member of the chain, and $\{(\{a_{r,i}\}, \{a_{r,i-1}\}, \tau)\}$ for $2 \leq i \leq n$, that join the remaining elements of $\mathcal{A}_R$. The connectivity between the rest of the team and the chain is promoted by directives $\{(\{a_k\}, \{a_{com}\} \cup A_R, \tau)\}$ for $a_k \in \mathcal{A} \setminus (\mathcal{A}_R \cup \{a_{com})\}$. The parameter Ω specifies a ratio of $3:1$ between the weights of the directives corresponding to the formation of the chain, and the latter. This decision is motivated by the fact that the formation of the chain is the key aspect of this strategy, and without it, the complete team might become permanently disconnected from the command center.

To promote the *DataMules* strategy, we selected a set of agents $\mathcal{A}_M$ to become the *mules*. Their purpose is to travel back and forth between the rest of agents and the command center. We specify two sets of directives, to promote the connectivity between the command center and the mules, and between the rest of the team and the mules. For the first set, we defined instant directives $I_1 = \{(\{a_m\}, \{a_{com}\}, \tau)\}$, for each $a_m \in \mathcal{A}_M$. For the second set, $I_2 = \{(\{a_k\}, \{a_{com}\} \cup A_M, \tau)\}$, for each $a_k \in \mathcal{A} \setminus (\mathcal{A}_M \cup \{a_{com})$. For each I_1 and I_2, a set of recurrent connectivity directives is also defined: $R_j = \{(I_j, \tau, \delta)\}$ for $j = 1, 2$, and with $\delta = 3$. The parameter Ω specifies zero weight (i.e., zero penalty) for the instant directives, and equal weights among the recurrent directives. This is motivated by the fact that for this specific strategy we are only interested in the recurrent achievement of the directives.

B. Scenarios

The scenarios are based on an area of size $700 \times 700\ m^2$. Fig. 6 shows the digital elevation map (DEM) and the distribution of vegetation of the area. The area has been decomposed into cells of $100 \times 100\ m^2$. We considered three different types of agents: (i) aerial robotic platforms, more specifically quadrotors, (ii) human rescuers, and (iii) air-scent dogs. To account for the wider mobility of aerial robots compared to dogs and humans, we define their possible sectors of size $200 \times 200\ m^2$ (i.e., all clusters are of 2 cells $\times$ 2 cells). For human and air-scent dog agents, the sectors are of same size as the cells. The traversability graphs allows the movement between sectors whose centroids are separated by a maximum distance of 290m, for aerial robots, and 150m for human rescuers and air-scent dogs. Aerial robots are characterized by their higher speed, which is not affected by terrain conditions, while their vision sensors are significantly affected by the amount of land cover (i.e., vegetation) and by light conditions. On the other hand,



(a) DEM, in meters (b) Vegetation: 0=sparse,1=dense

Fig. 6: Characteristics of the area considered in the experiments.

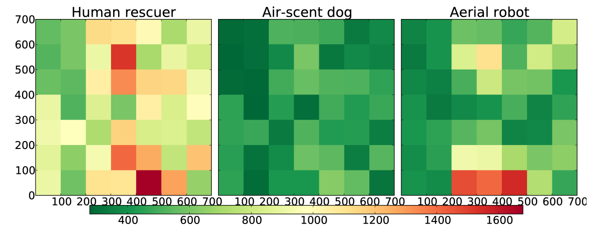


Fig. 7: Search efficacy as time required to fully cover a cell.

the mobility of human rescuers and air-scent dogs is heavily affected by the terrain conditions (e.g., slope and ruggedness), but their capability of sensing is quite robust to the presence of vegetation. Fig. 7 shows the way the search efficacy was defined at each cell, for each type of agent.

C. Results

We considered 12 problem scenarios, differentiated by the starting position of agents and the composition of the team. Specifically, we positioned the agents at each one of the four corners of the area, and composed teams with an equal number of agents for each type (i.e.,2,3,and 4), corresponding to team sizes of 6, 9, and 12 agents. Plans are computed for a time-span of 35 minutes, with $\Delta_t = 300$ seconds. When using the connectivity-aware planning, the aerial robots act as relays ($\mathcal{A}_R$) and as mules ($\mathcal{A}_M$) in each of the corresponding strategies. A maximum time of one hour was given to the solver to find the best possible solution. The nature of the solver also allowed to obtain the optimality gap of the given solution, which turned out to be 5% on average.

For each instance, we obtained mission plans for the unconstrained case and for both the RelayChain and DataMules strategies. When using the connectivity directives, we considered different values for the penalty factor $\lambda \in \{0.25, 0.5, 1, 10, 100\}$, representing different trade-offs between coverage and compliance of the directives. To analyze the quality of plans in terms of network performance, we use as metric the *network delivery ratio*, that is, the amount of data received at the base station divided by the total amount of data generated by the agents. We performed 5 simulation runs to account stochasticity, and compute the median value of the metric. Fig. 8 and 9 show the results for coverage and network performance respectively. In the figures, results for the 12 considered scenarios are organized column-wise, by increasing team size, and row-wise by the starting point of the mission. Results indicate that through the use of the connectivity-aware methodology we can greatly increase the quality of communication (i.e., the amount of data received at the base station) at very low expense of mission performance. We can also appreciate the impact of the increasing λ parameter over both coverage and network performance. As expected, the increase of λ generates solutions that obey

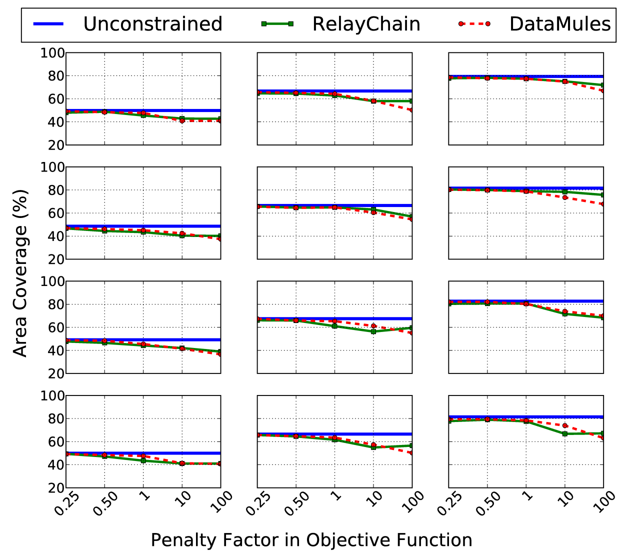


Fig. 8: Coverage performance of computed plans.

a larger number of directives, and therefore provides greater benefits in terms of communication at some expense of mission performance. We also note that this situation was not reflected in a very few instances. We believe that these cases are a consequence of the quality of these particular solutions, which did not follow the general trend of the experimentation. Additionally, it can be seen that, in general, the *DataMules* strategy provides greater communication enhancement in comparison with the *RelayChain*. We speculate that one of the possible reasons for this difference is the greater flexibility of the *DataMules* strategy, which enables the solver to easily find solutions that implement most of the connectivity directives.

In general, the results demonstrate the potential benefits of the proposed framework. The flexibility of the approach also allows to model a vast number of different strategies aiming at enhancing the communication performance. The two strategies considered in this evaluation are just a proof-of-concept of the effectiveness of the use of directives. Although the purpose of the analysis is not to determine which of both strategies is better in terms of coverage cost versus network performance, the results raise interesting issues such as the one of design of effective strategies that can be represented by a congruent set of connectivity directives.

V. Conclusions and Future Work

We propose a novel approach to deal with the joint problem of enhancing the communication and planning the activities of a team of mobile agents. The methodology introduces the use of connectivity directives whose (partial) compliance is expected to translate into beneficial conditions for data exchange.

The applicability of the approach was demonstrated in the context of wilderness search and rescue missions. To this end, we proposed the connectivity-aware mission planning, formalized by means of a mixed-integer linear program. We evaluated the connectivity-aware planning using sets of directives inspired in typical communication strategies used in these type of missions. Results indicate that through the use of the connectivity-aware planning we can greatly increase the quality of the communication at a very low expense of mission performance.

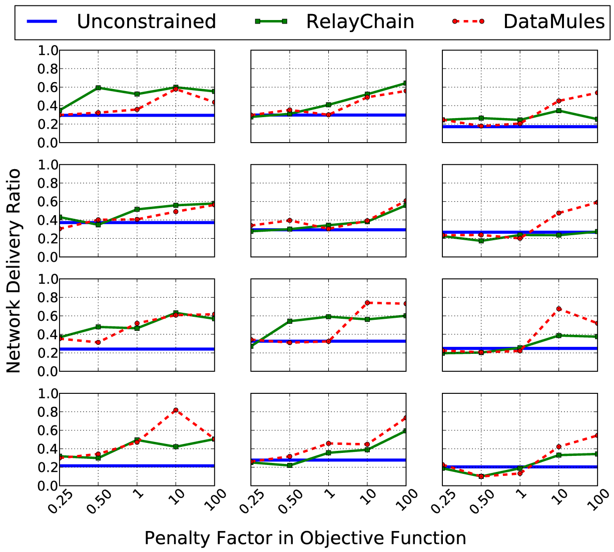


Fig. 9: Network performance results after simulations.

The proposed approach can also be used in an iterative receding-horizon manner [13], where mission planning is carried out over short planning horizons. In this way, the planner can accommodate the dynamic aspects of search and rescue missions, such as variations of the agents' estimated search performance (e.g., subject to weather conditions), the discovery of new hints about target location, and unexpected changes in the composition of the team. Under this scheme, mission plans are iteratively defined in stages, and new information acquired is included in the subsequent mission stages.

We believe that the results of the evaluation are promising, and that the approach can also be applied to other similar problems. In particular if there exists an implicit trade-off between communication and performance that is expected to be controlled. Future work includes a more extensive evaluation involving many different sets of directives, and over a larger number of scenarios. We also aim to extend the approach to cover scenarios where minimum connectivity guarantees are needed. To this end, the set of directives could be mixed together with a set of strong connectivity constraints.

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