TRAVERSABILITY-AWARE SIGNAL COVERAGE PLANNING FOR COMMUNICATION NODE DEPLOYMENT IN PLANETARY CAVE EXPLORATION

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ABSTRACT

In this paper we describe an automated planning system that selects the optimal target location to drop a communication node in an unknown cave environment to maximize communication coverage while minimizing the risk of violating safety constraints for all robots traversing the area based on local environmental and operational constraints.

1   INTRODUCTION

Planetary subsurface/cave exploration is one of the target capabilities in NASA's Lunar Surface Innovative Initiative (LSII) towards enabling human and robotic exploration on the Moon, as well as future operations on Mars. However, caves offer several technological challenges for robotic missions, including access, mobility, communication, power and autonomy.

Communication in a cave specifically has a high level of uncertainty in the reliability, capacity, and availability of the links between robotic explorers. Previous theoretical work [1] and preliminary field experiments [2] in linear tunnel configurations (e.g., Mueller Tunnel) have shown that a cave's geometry can cause large constructive and destructive fading effects in communication signals. In the constructive case, multiple signal reflections arrive at the receiving antenna aligned in phase, significantly increasing the signal strength. In the destructive case, these reflected signals arrive at the receiver out of phase, thus canceling each other out. Experiments showed that the transition between constructive and destructive can occur with a movement as short as the carrier wavelength, 12.5 cm in the case of WiFi. The authors of [8] formulate a distributed constraint optimization problem and demonstrate how micro movements in the order of a wavelength influence the network throughput up to 270% in their experimental setup.

Due to such uncertainty in communications and in the environment itself, future planetary subterranean missions will increasingly rely on autonomous capabilities for building communication infrastructure (e.g., repeaters, data stores) and for
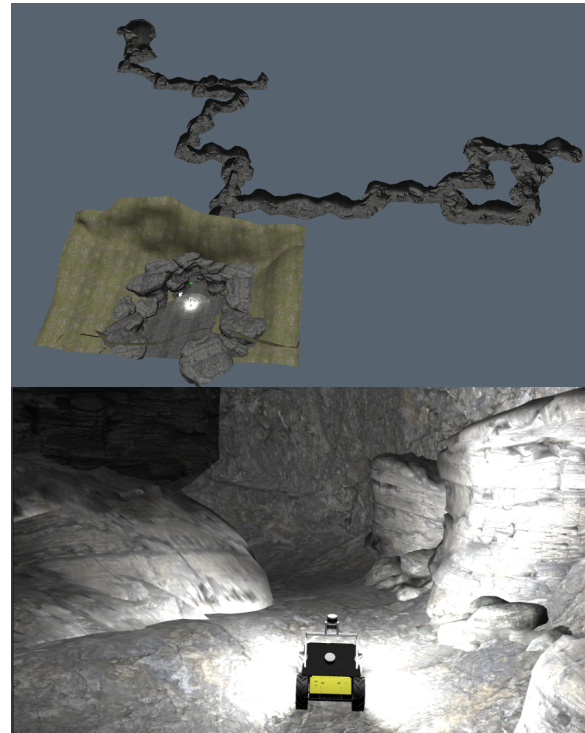

Figure 1: Simulated Cave Environment.

placing instruments and sensors (e.g. localization beacons, scientific instruments). Autonomy in multi-robot coordination in particular is a key mission enabler that would help robots to create and adapt a communication network to connect the robotic team to a base station (at the entrance of the cave) while the robots map and explore an *a priori* unknown cave environment.

One promising approach is to allow certain robots to *drop wireless communication nodes* (repeaters) along the way during exploration - a technique that has been actively used in recent research on robotic subterranean exploration such as in the DARPA Subterranean Challenge. However, one of the main challenges in dropping communication nodes is to decide where exactly to drop it to 1) maximize signal strength and available bandwidth between the target robots in the network given the aforementioned

communication link uncertainty while 2) minimizing the risk of violating safety constraints as the robot approaches the dropping location, and 3) minimizing the potential traversability hazards for robots exploring the same area. If traversability is not taken into account in the multi-robot traversability setting, communication nodes can easily become an obstacle, or even be damaged by robots driving over them.

Literature provides several efforts on addressing the aforementioned challenge (1), where the problem is usually formulated as a geometric coverage planning problem [3, 4], and communication-aware motion planning [5, 6, 7]. However, to the best of our knowledge, there is no technique for positioning communication nodes that also aims at a minimum disruption in the flow of the crossing robot teams (i.e., challenges (2) and (3)).

In this project we develop a hierarchical planning system that includes 1) *a global planning* approach to determine how many communication nodes to drop and what segment of the cave to drop them, and 2) a *local planning* to optimize the target placement location within a segment and the robot trajectory based on local environmental and operational constraints. In this paper, we focus on the local planning problem, where the system searches and determines an efficient target location to drop a communication node given a bounded area of the environment (e.g. a cave segment) and a set of reference nodes in the network (e.g. base station, a peer robot or another previously dropped communication node). The local planning process includes two phases: *information gathering* and *placement selection.* In the first phase, the robot is sent to the specified bounded area for collecting a higher resolution map of environment and signal strength measurements. The map and signal observation will be used to estimate and refine a communication signal strength map (SSM) of the local cave segment. Herein, the system uses existing stochastic models [1][2] to predict and refine the SSM as the robot collects signal observations. In the second phase, we frame the selection and path planning processes as an optimization problem that takes into account i) an estimated SSM of the cave segment, and ii) the 3D map of the cave segment to evaluate robot team traversability, i.e. the most likely paths and flow.

We present a prototype of the proposed local planning system, including the SSM estimation and the optimization process. We show preliminary results from simulated multi-robot cave exploration scenarios focusing on the selection phase. Figure 1 shows the simulated cave environment used to test our approach.

The top image shows the global view of the entire simulated cave and the bottom image shows the robot tasked to deploy the communication node and a portion of the cave's interior.

2   PROBLEM STATEMENT

Given a bounded area of an environment (e.g., cave segment), a robotic platform capable of carrying and deploying communication nodes, a traversability map, a communication signal strength map (SSM), and the information about the locations of other communication nodes already deployed in the environment, we aim to design a solution that allows a robot to autonomously select an optimal location to place a new communication node within that bounded area that both 1) maximizes the local signal coverage and 2) reduces the disruption and risk of the robot's operations.

Consider Q a 2D grid representing the robot's local view of the world. The *Traversability Map T* is a 2.5D grid map (see Figure 2), where each cell in this grid represents the probability that the corresponding cell in Q is traversable by the robot in consideration. The traversability map considers positive (walls, rocks), negative obstacles (holes, cliffs) and other features found in cave terrain (e.g., steep slopes) [9], and cave areas not yet explored are labeled as unknown. We define the *Obstacle Space $O \subset Q$* the set of grid cells whose corresponding probability value in T is zero and the *Drop Space $D = Q - O$*, is the set of valid positions p where a communication node can be placed on Q. The *Reference Space R*, subset of $\mathbb{R}^2$, contains the locations of the communication nodes already placed in the world, which is used to compute the signal strength map *SSM*.

The objective is then to use this information to allow the robots to autonomously select a location $p^* \in D$ to place a communication node that satisfies both desiderata 1) and 2).

3   LOCAL PLANNING APPROACH

In this section, we describe the two phases of our approach, *information gathering* and *placement selection*, and the operation restriction regarding *deployment*.

3.1   Information Gathering

It is expected that the given bounded area of the environment, that the robot is tasked to deploy a node, is not fully known in advance. Thus, gathering more information about traversability and communication constraints is key for an effective communication node deployment.

The first phase of the proposed local planning approach consists of planning the path to a given, location/cell $p_0 \in D$ (provided by the global planning process) within the bounded area, we call p_0 as the query location. From that location, the robot performs coverage path planning to execute a motion pattern, or any combination of patterns, for no more than a predefined time threshold - herein, we consider a library of motion patterns (e.g. zig-zag, spiral, random walk, wall follow) [12]. Determining the specific patterns to be executed in order to increase information gathering is out of the scope of this paper.

As the robot performs the motion patterns, it constructs and refines the traversability map T. It also collects signal strength readings from the existing, previously deployed communication nodes. The information/data gathered during this phase is used as the input to the selection process as follows.

The location p_0 is optimized based on the objectives of the mission, and therefore, we want the robot to deploy the communication node near p_0. We restrict the placement location to be within a predefined distance $d_p = 10m$ away from p_0. Accordingly, we also restrict the information gathering to collect data within $10m$ of p_0.

3.2   Selection

We formulate the placement selection problem as a discrete multi-objective optimization. A *criterion vector* is assigned to each cell in D and it is used as the criterion for selection (the set of criteria used in this project is described later in this section). Consider C to be the set of criterion vectors in $\mathbb{R}^2$ such that $C = \{c \in \mathbb{R}^n : c = [c_1(p), c_2(p)] | p \in D\}$. We use Pareto Optimality [11] to reduce the set of valid placement locations by eliminating locations from D that are sub-optimal. A placement location is eliminated if there is another placement location that has a better score c_i in one criterion and at least the same score in the others. We compute the Pareto Optimality as:

$$A(C) = \{c' \in C : \{c'' \in C : c'' \succ c', c'' \neq c'\} = 0\}.$$

$A(C)$ maps D to a refined subset of the drop space $D^* \subset D$ where all the elements are equivalent according to our selection criteria.

We design our criteria based on the following desired behaviors of our problem.

3.2.1. Maximize signal strength and coverage:

To enable global mission planning and real time risk management, it is desirable for the robots to maintain reliable communication links with the base station for most of the duration of the mission. There are two objectives to be considered here: 1) maintain signal
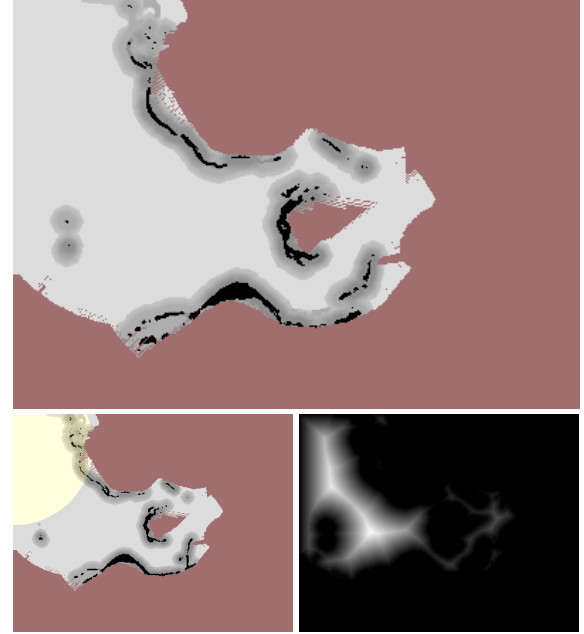

Figure 2: Top image: Traversability map; unknown cells are red, obstacle cells are black and the traversable cells are in shades of gray *Bottom left image: Traversability map augmented to depict areas with communication coverage; the cells in yellow color have* SNR > 37 dB. *Bottom right image: distance transform (*higher distance values are brighter than lower distance values)

coverage uninterrupted with previously deployed nodes and explored regions; 2) maximize signal quality/strength with other comm nodes in the network (including base station); and 3) to maximize the local signal area covered by the node to be placed.

We use a probabilistic communication model derived for linear tunnel environments [2] that relates the distance between two communicating nodes (transmitter and receiver) to signal to noise ratio (SNR). In such a model, if the distance between transmitter and receiver is greater than 20 m, the SNR maps to a value $\leq$ 37 dB, whose estimated bandwidth (BW) is $\leq$ 1Mbps. Hence, in this paper we assume that if a cell in Q has SNR $\leq$ 37 dB, it does not have enough bandwidth for effective communication. Figure 3 shows in yellow the area covered by a communication node already placed/deployed.

A cell p whose SNR value is in the interval (0, 37], is in the transition from a covered to an uncovered area communication-wise. Therefore, to maintain uninterrupted communication, it is desirable that a large part of these transition cells are covered by the communication node to be placed/deployed.

We design the criterion c_1 based on how many transition, uncovered and covered cells are reached by the new communication node:

$$c_1(p) = \sum_{\forall q \in Q} comm\_score(q)$$

such that:

$$comm\_score(q) = \begin{cases} 1 & \text{if } 0 < SNR(q) \leq 37 \\ 0.5 & \text{if } SNR(q) = 0 \\ -1 & \text{if } SNR(q) > 37 \end{cases}$$

The above criterion allows us to focus on areas/cells that do not yet have good signal and avoid those that already have good signal/coverage.

3.2.2. Reduce risk of disruption in robot's operations:

Random or poorly planned placement locations, such as placement in narrow corridors or in regions that are frequently visited by other robots, will force their path/motion planners to either reduce the speed at which robots are navigating while in these regions to avoid collision with the communication nodes or to change their trajectory completely to a possibly less efficient one, if, luckily, one exists. To prevent these issues, we formulate the criterion c_2 atop the concept of *Distance Transform (DT)* [10]. In our application, the distance transform maps each free (non-obstacles) cell into its distance to the nearest obstacle cell $O \subset Q$. In Figure 3, we have the traversability map T in the top image and its corresponding distance transform map in the bottom right image - higher distance values are brighter than lower distance values. *Narrow corridors* are darker compared to open areas since, for each position p in a corridor, the distance to the closest obstacle is shorter than in open areas. Therefore, we use DT as one of the selection criteria:

$$c_2(\boldsymbol{p}) = DT(p),$$

where:

$$DT(p) = min\{d(p,o) \mid p \in Q, o \in O\}.$$

3.2.3. Selection method:

The refined set D^*, result of applying Pareto optimization using c_1 and c_2 and then contains a set of good deployment locations. Because of c_1, many of the deployment locations lie in areas often visited/used by other robots (which is undesired). If we can find more than one $p \in D^*$ whose distance to a wall is lesser than 0.5 m, we select p^* as the one closest to p_0. If no $p \in D^*$ is close to the wall, we project all the points

in D^* to their closest wall and, as before, select p^* as the one closest to p_0.

3.3　Deployment

The location p^* is finally used to place a new, stationary, communications node. Herein, the robot plans its path from its current location (i.e. the end location of the information gathering phase) to the selected location p^*. When the robot is located at p^*, it performs the comm node deployment behavior.

4　EXPERIMENTAL RESULTS

We focus our preliminary experiments on demonstrating the adaptability of our *selection method* and understanding its limitations. A thorough analysis of the proposal local planning system with respect to all the phases is left for future work.

We use a set of comm node deployment scenarios in a simulated 3D cave environment to test the feasibility of the proposed selection process. Herein we used a synthetic cave model from DARPA Subterranean Challenge repository (SubT Tech Repo).[1] For each scenario we set p_0 (query), illustrated as a red dot in Figure 3, top image, and run our selection algorithm to select the target p^* drop location, illustrated as a green dot in Figure 3, top image. The blue circle represents the distance restriction $d_p = 10m$ from p_0. After selection is completed, we run the robot's comm deployment behavior to move the robot to p^* and drop a comm node. Figure 3, bottom image, shows the communication node on the ground (indicated by the yellow arrow) deployed by the simulated robot.

Figure 4 shows four representative scenarios and depicts the results from the selection method. In the top image, the query node is far from the region covered by any element from reference space R, hence the optimization is equivalent to simply select a location that maximizes c_2. In the second image (top-down), the bounded region starts exactly in the transition between the covered and uncovered regions with respect to communication signal, hence, criteria c_1 and c_2 are equally determining the optimized location. In the third image, the query node is inside a covered area, leaving very little space for optimization. Finally in the bottom image, there is no space for optimization, and the drop location is set to be in the very limited location that is not already covered.
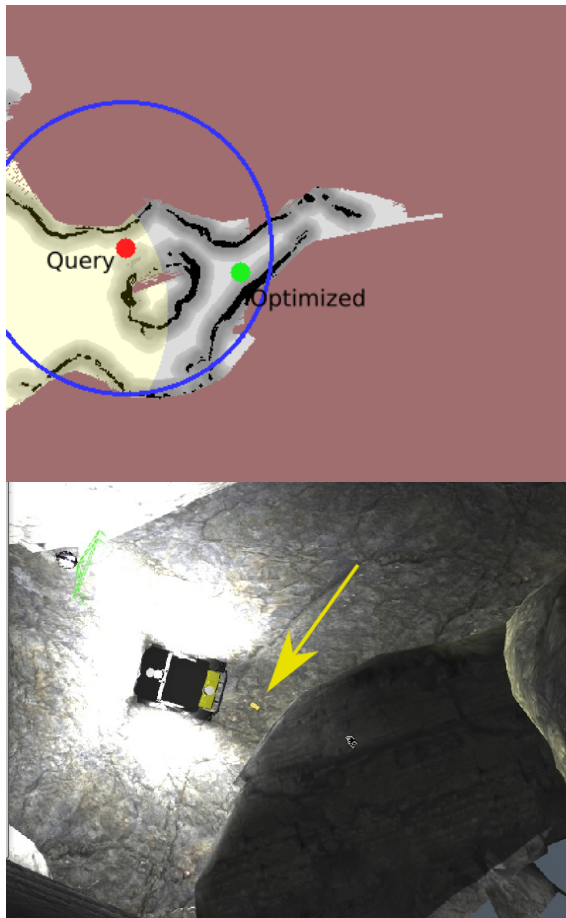

Figure 3: Communication node deployment, including the selection process (top) and simulated deployment of comm node (bottom).

A very simple modification in our approach, that have potential to a large improvement in performance is to allow the robot to explore the environment beyond d_p and suggest a target segment based on the local measurements and assessment. This would be very useful in cases like the top image of Figure 4, where the robot could search for the transition areas; and in the case of the bottom image, where no communication node is actually required in the bounded region.

5   CONCLUSION

In this work we demonstrated autonomy in the selection and deployment of communication nodes in a simulated cave environment. We describe preliminary results obtained from simulated scenarios in cave environments to test the feasibility of the proposed.

For future work, we will expand our experiments to analyze the performance of the complete local planning system, both in simulation and in real cave
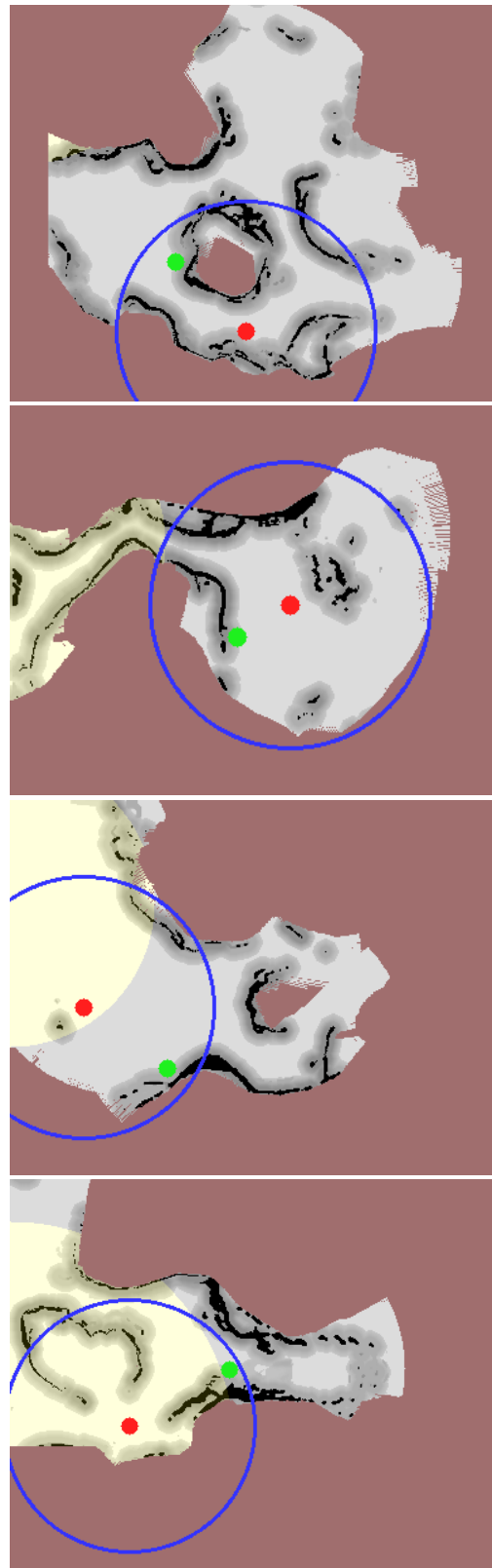
Figure 4: Deployment scenarios with the respective selected locations (green dots) and initial queries (red).

environments. We will look into using signal strength map models that consider complex, non-linear cave structures. Investigating methods to refine/adapt such models online based on measured communication signals during information gathering phase (and during exploration in general) is also a promising and key direction. Furthermore, multi-robot control algorithms and resiliency aspects in evolving multi-robot networks [13] (e.g., failing robots and communication nodes) can be combined with this approach in future works.

Acknowledgement

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