Final Report: Distributed Multi-Robot Exploration of a GPS-Denied Environment

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1 Introduction

Exploration of unknown environments by a single robot is a very common problem. Exploration is a critical component in search and rescue operations among others. In these situations, a single robot is limited. These limitations include battery life, sensing range, and robustness.

To account for these limitations, multiple robots can be deployed to cooperatively explore an environment. One way to do this is to have a central coordinator which can communicate with each of the robots. An example of this can be found in [1], [2]. There are obvious limitations to this. The biggest limitation is the fact that communication link between the coordinator and robots is often weak or unreliable. This method also causes significant scaling issues. The coordinator must receive map information from each of the robots. As the number of robots grows, the bandwidth of the communication link between the coordinator and robots becomes a bottleneck.

Distributed methods for multi-robot exploration address these issues by removing the need for a central coordinator. These methods only rely on robot to robot communication to split the exploration task. In [3], the authors have each robot partition the exploration space upon interaction.

A key limitation of the previous methods is that they assume the robots are localized in a common frame. In many situations this is not possible. The method described in [4] accounts for this by using a particle filter to merge the map of one robot into a global map. While this does address the issue of GPS-Denied Environments, it is very expensive from a communication point of view. This introduces scaling issues.

In my course project, I would like to address these issues in a bandwidth efficient manner. The goal is to develop a highly scalable multi-robot exploration algorithm capable of operating in a GPS-denied environment.

2 Problem Formulation

2.1 Requirements

The goal of this algorithm is to explore an initially unknown environment with n robots. There exists no global positioning system to localize each robot in a common frame. The starting position of each robot is not known initially. Each robot can only communicate with another robot when in line of sight. The communication bandwidth is very limited (¡ 250kbps). Each robot is equipped with a 360 deg depth sensor with range r_s. Each robot can measure the relative transformation between its neighbors when in line of sight and in communication range, r_c.

Figure 1: Example of the exploration problem described. Occupancy Grid from [5].

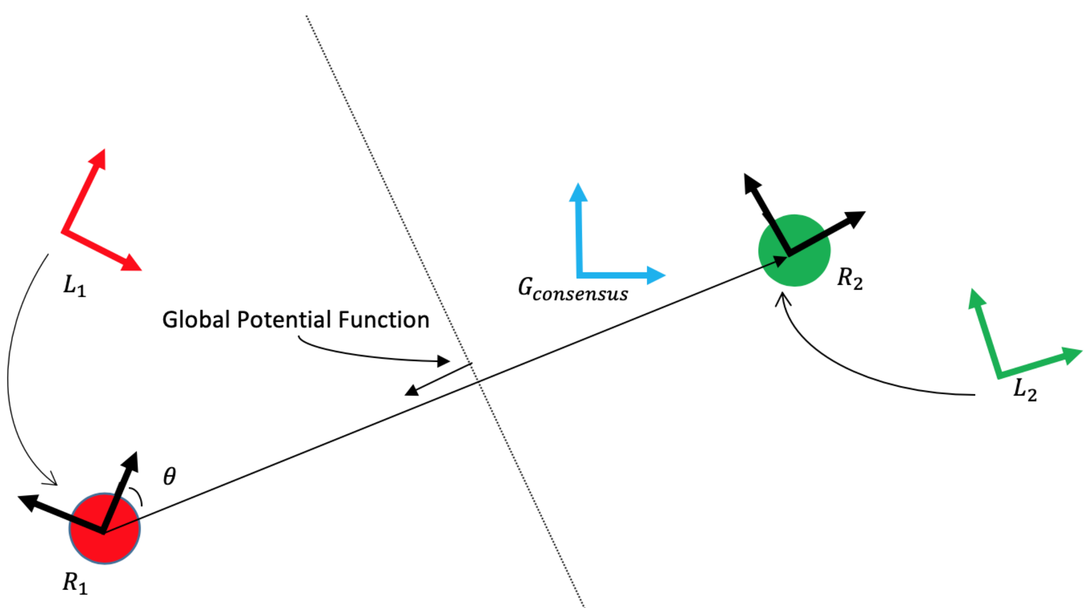

Figure 2: Since all robots start in arbitrary and unknown positions, a common global frame consensus must be found between all robots. This consensus allows the robots to share information defined in a consistent frame.

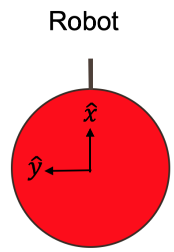

Figure 3: Robot coordinate frame

2.2 Robot Dynamics

$$\dot{x(t)} = f(x(t), u(t)) \tag{1}$$

$$u(t) = \begin{bmatrix} v_x(t) \\ \dot{\theta(t)} \end{bmatrix} \tag{2}$$

in equation 2 v_x refers to the forward velocity of the robot, and $\dot{\theta}$ refers the z axis angular velocity of the robot. In this problem, the motion of the robot will be constrained to $SE(2)$.

2.3 Objective

Any exploration algorithm can be summarized by an information maximization algorithm. Information, in the context of this problem, is defined as understanding of the environment.

First, we must choose a map representation. A common choice for a 2D problem like this is an Occupancy Grid. An example of this can be seen in 1. An Occupancy Grid is an array of grid cells with an assigned probability of being occupied. If the cell is occupied, the probablity is > 0.5. If the cell is unoccupied the probability is < 0.5. If no information is known, the cell is $= 0.5$. Let's define the global map, M_G, as an occupancy grid.

$$p = f(M_G, i)$$

The function f is a mapping from the occupancy grid, M_G, at point i to a probability, p. $p \in \mathbb{R} : 0 \leq p \leq 1$ and $i \in \mathbb{Z}^2$.

The depth information sensed by each robot can be used to update the occupancy grid in a Bayesian manner. An example of this can be seen in figure 4.

We can now define an information function R.

$$R(M_G) = \sum_{i \in \mathcal{I}} \|(f(M_G, i) - 0.5)\|^2$$

(3)

In equation 3, $\mathcal{I} \in \mathbb{Z}^2$ is the set of all points on the occupancy grid M_G. We can now write the full objective.

$$\underset{u_1(t),\ldots,u_n(t)}{\arg\max} \; R(m(u_1(t), \ldots, u_n(t))) \tag{4}$$

In the objective function 4, the function $m(u_1(t), ..., u_n(t))$ is a Bayesian update on the initially unknown M_G.

3 GPS-Denied Multi-Robot Frontier-Based Exploration

Since information is defined as the distance from the unknown occupancy probability, 0.5, We know that information is maximized when all reachable unknown space is known to be either occupied or unoccupied.

A common method for exploring environments is frontier based exploration. A frontier is defined as a point on the occupancy grid which is unoccupied and adjacent to an unknown point. If a robot always drives towards a frontier while running a SLAM algorithm, it will eventually explore the map fully and therefore maximize information gained.

The question is which frontier does the robot move towards. For single robot exploration, a simple solution would be to move towards the closest frontier at all times. However, when there multiple robots, this is no longer a good choice as it would result in a lot of duplicate exploration.

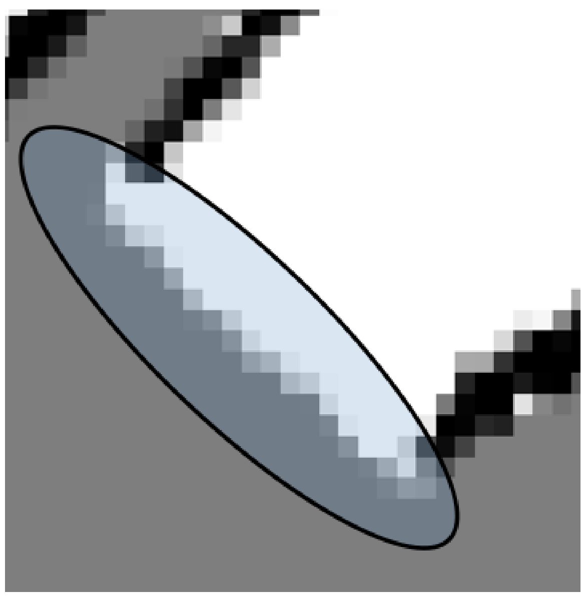

Figure 4: Bayesian updated occupancy grid during single robot exploration. The region circled is an example of a *frontier*. These frontiers represent the boundary between explored and unexplored areas.

In this work, I present a method for establishing globally consistent potential functions each robot can use to bias their exploration in a way which reduces redundant exploration.

3.1 Global Frame Consensus

Initially, the robots all assume that they started from the origin of the common global frame. This is typically far from the truth. It is necessary that all robots achieve consensus on a common global frame they are localizing with respect to.

There are multiple ways to do this, one way is to perform map alignment on all robots by transferring the local occupancy grids of each robot to all other robots. While this would work for a small number of robots, it is not scalable.

Figure 5: An example of an April tag. These tags act can easily be identified, and have a code associated to each of them. [6]

In order to achieve a common frame consensus between all robots, I assume that we can measure the relative transformation between robots. In a real system this could be achieved easily and robustly using April tags [6].

Another option for measurement would be a bearing measurement. The difference is a bearing measurement contains only one degree of freedom, and makes multiple observations necessary however, this does not present a problem.

let R_i, L_i, and G_i be the i^{th} robot's body frame, local frame, and global frame estimate respectively. Initially, each robot knows ${}^{L_i}T^{R_i}$, the transformation from the local frame to the body frame, is the unit transformation. However, each robot is infinitely uncertain about ${}^{G_i}T^{L_i}$.

Then, when robot i and robot j are within both communication and sensing range of each other, they both can measure ${}^{R_i}T^{R_j}$, the relative transformation between the two robots.

Using this measurement, a residual can be defined.

$$J_{ij} = Log[{}^{R_i}T^{R_j}({}^{G_j}T^{L_j}\,{}^{L_j}T^{R_j})^{-1}({}^{G_i}T^{L_i}\,{}^{L_i}T^{R_i})] \in se(2) \tag{5}$$

This residual is effectively the difference between expected and measured relative transformations. We seek to perturb the transformation ${}^{G_i}T^{L_i}$ such that the squared L2 norm of this residual is minimized.

To make minimizing this residual easier, I split it into its rotation component and translation component.

In this algorithm, I choose to only move $\frac{\delta x}{2}$ each update where δx is the perturbation of ${}^{G_i}T^{L_i}$ which minimizes the residual. This results in good convergence of the global frame estimate for each robot to a common frame.

3.2 Exploration Potentials

To drive the robots towards globally unexplored frontiers, a potential function was created with inspiration from [2]. When two robots communicate and sense each other, they both create an equal and opposite potential field defined in the common frame whether or not consensus has been reached. This potential field takes the form of an exponential boundary drawn between both robots in the common global frame. A more visual description of this can be seen in figure 2.

Each potential ϕ_i is defined by a point, p_i, and normal vector, $\hat{n}_i$, in the common frame.

$$\phi_i(r) = exp(-\hat{n}_i^\top (r - p_i)) \tag{6}$$

The frontier which minimizes the sum of all global exploration potentials is chosen to be explored.

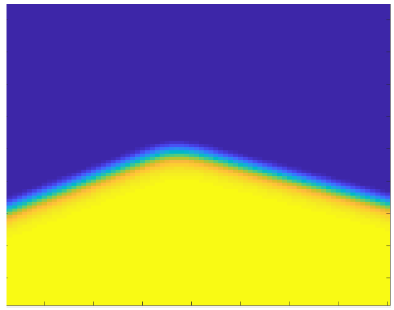

Figure 6: Example of the total exploration potential field for a single robot. Yellow is high cost, and blue is low cost.

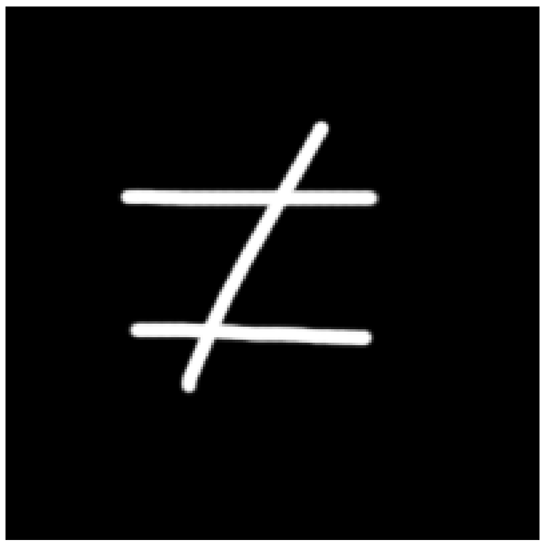

Figure 7: A simple map.

4 Results

Two maps were used to evaluate the algorithm. These maps are created from images were black is unoccupied, and white is occupied. Both maps are 100 X 100 meters.

Robot positions and rotation are initialized randomly in a 10 X 10 meter box in the center of the map. During the exploration, I compute the percentage of map explored by computing the number of unoccupied nodes in the ground truth map, and the number of unoccupied nodes across all robot local maps. When these numbers are the same all occupied space has been observed across all robots.

Figure 8: A complex map.

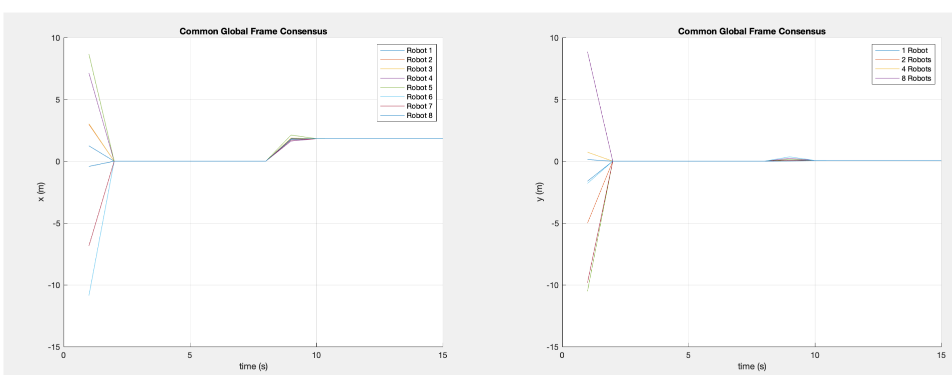

Figure 9: The common frame position consensus across 8 robots over time. Initially, the communication graph is strongly connected which results in very fast consensus.

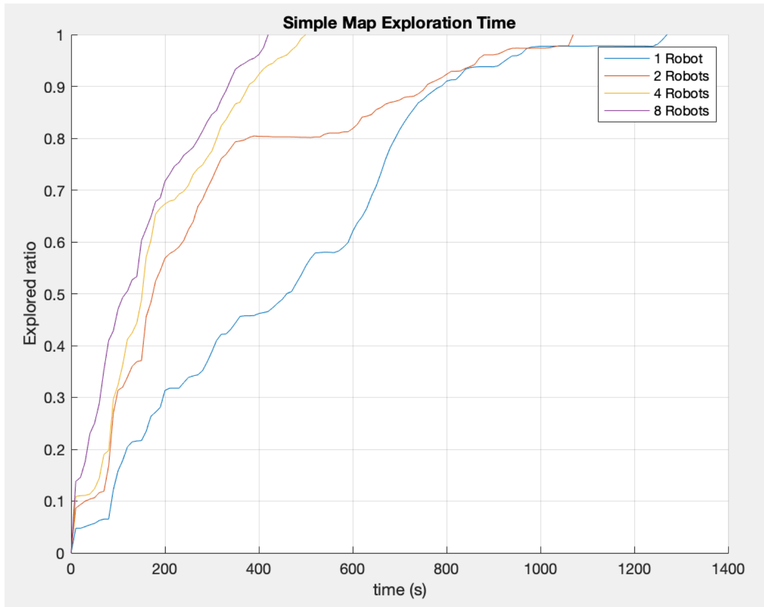

Figure 10: As the number of robots increases, the map is explored more quickly.

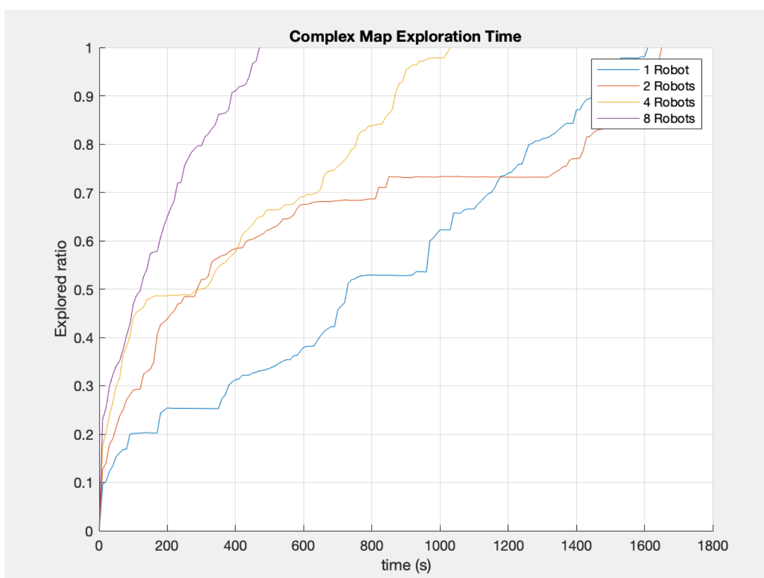

Figure 11: When the exploration occurs on a more complex map, we see that after the second robot is added, the exploration time actually increases. This can be explained by the complexity of the map forcing robots to follow relatively inefficient trajectories. However, once 4 or more robots are used, the exploration time decreases drastically.

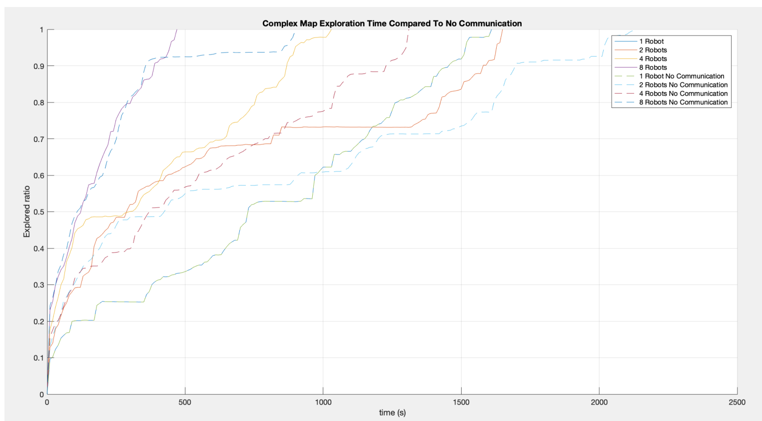

Figure 12: Finally, I compare the exploration times when the robots can not communicate with each other. We can see that when the robots can communicate there is significant performance increase across the board. If we look at the 8 robot case, we see that initially the no communication and communication cases perform similarly until the end of the exploration. At that point, the no communication case slows significantly. This is because each robot is not aware of where other robots are exploring so more redundant exploration occurs.

5 Conclusion and Future Work

In this report, I show that my method for distributed multi-robot exploration in a GPS denied environment achieves its goal of exploring an unknown environment with n robots which initially do not know their starting position.

This method is highly scalable since the communication complexity is constant for all robots at all times. By defining exploration potentials in the fictional common global frame, I ensure that the potential functions are never invalidated by a global frame consensus updates.

I was able to show that this method benefits from more robots even in a complex environment without the need for expensive robot to robot communications.

In the future, I would like to generalize this method to 6 degrees of freedom. This should be trivial from a global frame consensus perspective since the same update would apply if the right jacobian of SE(3) is used, but the potential functions would likely need to be modified.

References

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