ROB 530 Project: Multi-Agent Localization

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***Abstract*—This paper investigates the accuracy and confidence of multi-agent localization given different levels of access to information, including odometry measurements, landmark measurements, total inter-agent communication of all information, and filtered communication of information. Our results indicate that the optimal conditions are letting robots access both odometry and landmark measurements, as well as having them broadcast information that they are confident of to other robots. Our git repository can be found at https://github.com/joek5555/ROB530Project. The UTIAS data set used is open-source.**

I. Introduction

In many scenarios, robots cannot use absolute positioning techniques such as GPS for their own localization problem, such as in mountain caves, on missiles, or in complex natural environments such as underwater. So being able to simultaneously localize and generate a global map has been an important ability of mobile robots.

The application of Extended Kalman Filters (EKF) in SLAM has been widely studied in recent years, but its computational complexity makes it difficult to meet the requirements of large-scale map construction [1], [2]. On the other hand, the particle filter uses a series of sampling points and generating particles, and it can describe arbitrary probability distribution. The particle filter has a unique advantage in parameter estimation and state filtering of non-Gaussian, non-linear time-varying systems [3]. They have been applied not only in single-robot localization and mapping, but also in multi-robot cases. In this paper, we discuss the application of particle filters in multi-robot localization.

The dataset used in this project consists of 9 sub-datasets. The data were produced with a set of mobile robots in a 15m×8m sized rectangular, visually flat indoor space with 15 static landmarks. Each dataset contains timestamped odometry (linear and angular velocities) and range-bearing measurements for each robot.

II. Related Works

In [2], the authors use particle filters to help localize robots in an environment where the landmark locations are unknown. To accomplish this, separate particle filters are used to track the robot location and the landmark location. In this paper, for every particle in the robot particle filter, there is a separate particle filter for each landmark. Then, as the motion model and measurement model is applied to each robot particle, the weights of the corresponding landmark particles are changed. Our project implements this slightly differently. Each robot only has 1 set of particles for each landmark instead of a set of particles per robot particle. When a landmark is detected, the estimated location of that landmark with respect to each particle in the robot particle filter is combined together to form the landmark particle filter. [5] also uses separate particle filters to track landmarks and robot locations.

In [6], the authors discuss the usefulness of sharing feature points detected in the environment between multiple robots attempting to localize themselves. However, it emphasizes that, in real time operations, the amount of information that can be feasibly transmitted and processed may be less than the information observed. This paper uses a method to optimize which information is shared based on what information will localize the robots the best. In our project, the uncertainty in detected landmarks must be less than some threshold before the landmark location is broadcasted. [4] also discusses how to optimize what information to share between robots to maximize accuracy.

III. Novelty

Other research teams have tested how well multiple robot systems can localize themselves under communication constraints. [2] seeks to minimize the number of bits for every message that every robot sends. [1] allows sensors with less variance to send messages with greater resolution and thus more bits. Our approach build off of these ideas. All robots will transmit their confidence in their own localization, then each robot will use a message transmission strategy based on this information. Other research teams have tested how well multiple robot systems can localize themselves under communication constraints. [2] seeks to minimize the number of bits for every message that every robot sends. [1] allows sensors with less variance to send messages with greater resolution and thus more bits. Our approach will build off of these ideas.

To address the limited bandwidth constraint, we prioritize robots with greater confidence in their own localization, but we do this by limiting the number of messages that each robot sends and limiting how many robots a message is sent to. We additionally apply a distance constraint, which was not done in the other papers that we surveyed.

IV. Methodology

A. Motion and Measurement Models

For the motion model, at each time step, the robots' positions are updated using their measured linear and angular velocities, $\hat{v}$ and $\hat{\omega}$, respectively. (x_k, y_k, θ_k) denotes the (x, y)-coordinates (Cartesian) of the given robot at iteration k, and θ gives the heading. We use the following equations to update the pose at each step:

$$\begin{aligned} x_{k+1} &= x_k - \frac{\hat{v}}{\hat{\omega}} \sin(\theta_k) + \frac{\hat{v}}{\hat{\omega}} \sin(\theta_k + \hat{\omega}\Delta t) \\ y_{k+1} &= y_k + \frac{\hat{v}}{\hat{\omega}} \cos(\theta_k) - \frac{\hat{v}}{\hat{\omega}} \cos(\theta_k + \hat{\omega}\Delta t) \\ \theta_{k+1} &= \theta_k + \hat{\omega}\Delta t + \hat{\gamma}\Delta t \end{aligned}$$

where $\gamma = 0$ (needed to allow the particle filter to properly estimate the new heading). We also need to consider that each robot's measurements have some noise associated with them:

$$\hat{v} = v + \mathcal{N}(0, \alpha_1 v^2 + \alpha_2 \omega^2)$$
$$\hat{\omega} = \omega + \mathcal{N}(0, \alpha_3 v^2 + \alpha_4 \omega^2)$$
$$\hat{\gamma} = \gamma + \mathcal{N}(0, \alpha_5 v^2 + \alpha_6 \omega^2)$$

All parameters α_i are specific to each robot depending on their sensors.

For the measurement model, we also have to consider the robots' sensors giving noisy measurements. The robots use their sensors to identify both landmarks and other robots. When something is identified, the sensors provide both a distance and a bearing (in the body frame), along with some additive Gaussian noise.

B. *Particle Filter Basics*

The particle filter we designed maintains a distribution of particles, each representing a potential pose of the robot and thus consisting of $x, y,$ and θ parameters. In addition, each particle has a weight associated with likelihood, and the particle filter maintains and updates the itself as the robot takes actions and measurements of its environment. The cycle of the particle filter is as follows:

1) When the robot moves, the noise and uncertainty associated with the motion model propagates the particles of the particle filter outwards, resulting in less precision on where the robot is located and expanding the particle cloud.
2) When the robot takes a measurement of a landmark, since each particle is a representation of a hypothetical robot pose, each particle also has its own idea of where the landmark is located. This creates a particle distribution for the location of the landmark. The mean of this distribution can be used to update the weights of the particles in the robot's particle filter by calculating the likelihood of each particle.
3) Finally, based off of the top 30-50% of particles, a new sampling of particles is drawn, with some added variance in the efforts of avoiding particle deprivation, where the particle cloud becomes dense and gets "stuck" on a single point that may not be accurate to the real location of the robot, and is very hard to recover from.
4) Now, the particle cloud is denser and closer to the true location of the robot. Repeat step 1.

C. *Particle Filter Resampling*

After a measurement step, each particle in the distribution is weighted according to the likelihood that the particle accurately represents the state of the robot or landmark at the given time. After a few update steps, it is very likely that the weight of most of the particles will be reduced to near 0, while only a few particles represent the region in the data that is most likely. It would be better if the particles were distributed in a way such that each one had the same weight but more particles were located in the regions that are more likely. This is what the low variance resampling algorithm accomplishes.

However, the low variance resampling algorithm will get rid of particles with a low weight, which can lead to a loss of diversity. We noticed that, in practice, the particle filter would often converge to a small variance close to but not including the groundtruth. Thus, to prevent a loss of diversity, Gaussian noise is introduced back into the particle distribution. In the low variance resampling step, after the particles have been selected but before their weights have been normalized, the particles are sorted by weight. A percent of the highest weight particles are set apart and averaged (30% to 50% worked well in practice). Then the rest of the particles are replaced with particles sampled from a Normal distribution with the mean of the averaged top particles and a set variance. This method worked well in practice, although a downside is the percent of top particles selected and the variance in which particles are sampled from must be fine-tuned.

D. *Landmark Belief Sharing*

To add the collaborative aspect to this multi-agent localization algorithm, we implemented the sharing of landmark data between robots. Specifically, if robot A detects robot B, then robot B shares its particle filter information for each landmark it has detected. This way, robot A can have a "second opinion" of what its environment looks like and therefore be able to localize itself better. However, there is such a thing as over-sharing with landmark data. If a robot is uncertain of a landmark's location, sharing that data with another robot may not help it localize itself better and may even be detrimental to localization efforts. In the figure below, it can be seen that the landmark with large variance should not be shared with other robots.

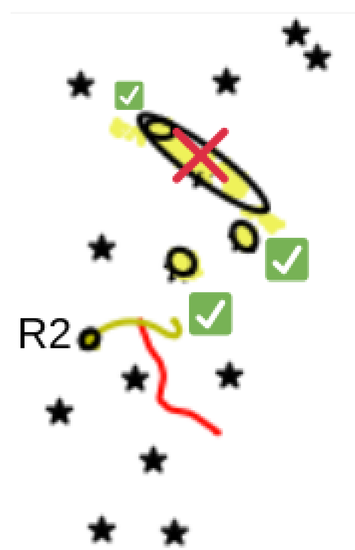

Fig. 1. Robot 2 is highly certain of the location of three landmarks, but is highly uncertain of the location of the last landmark.

As such, to ensure only quality information is shared to other robots, we implement a "confidence" metric that examines the diagonal elements of the landmark's $3x3$ covariance matrix, where the top left element is the variance of x, the middle element is the variance of y, and the bottom right element is the variance of θ. A confidence value $c \in [0, 1]$ is inversely proportional to the values of these variances, and a confidence of 0 means a variance value of 1 for x or y, or π for θ. Therefore, a nonzero confidence has less than these values for all parameters. We elected a 90% confidence as the minimum threshold rating for broadcasting landmark information, and will discuss the results of this experimentation in the next section.

V. Results

We tested the results of our particle filters by using the UTIAS dataset. We ran two robots for one minute, then compared the results with the groundtruth values given in the dataset. First, we ran both robots using only odometry information. This serves as a baseline to see how well other methods can improve on this. Figures 2 through 5 display these results.

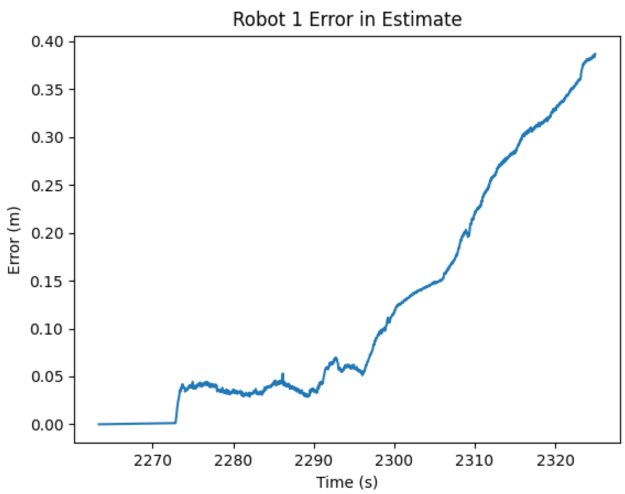

Fig. 2. Robot 1 error vs time using only odometry.

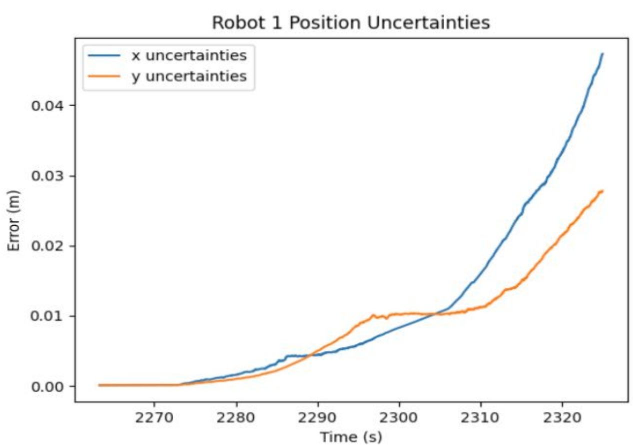

Fig. 3. Robot 1 x and y uncertainties with only odometry.

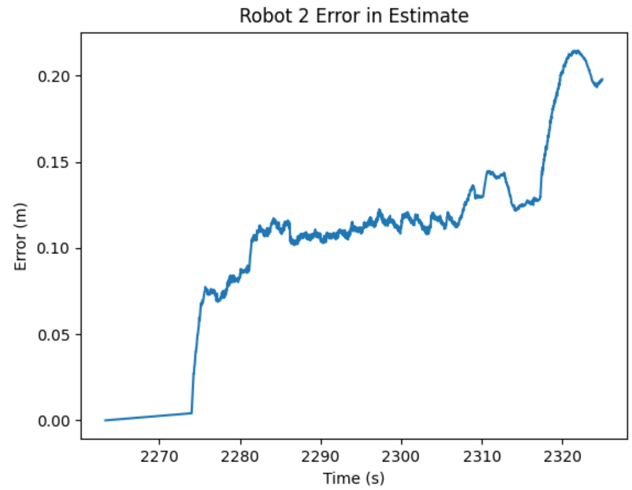

Fig. 4. Robot 2 error vs time using only odometry.

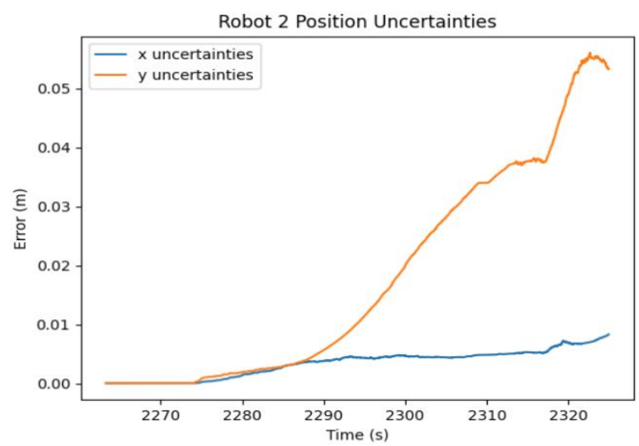

Fig. 5. Robot 2 x and y uncertainties with only odometry.

Next, both robots were run with access to both odometry and landmark information. In this test, robots were not allowed to communicate with each other. Figures 6 through 9 display these results.

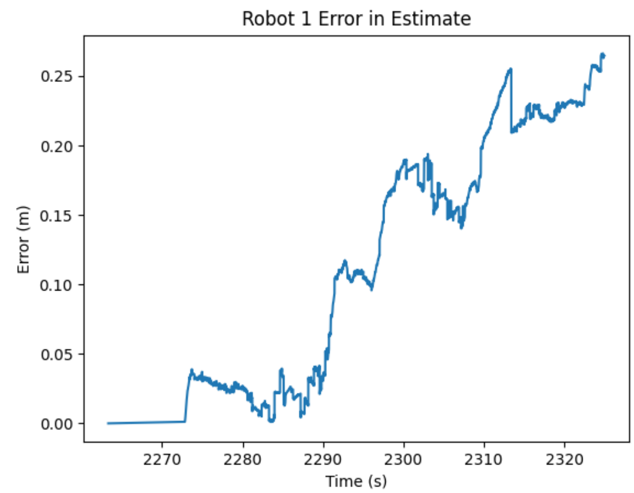

Fig. 6. Robot 1 error vs time using odometry and landmarks, but no communication.

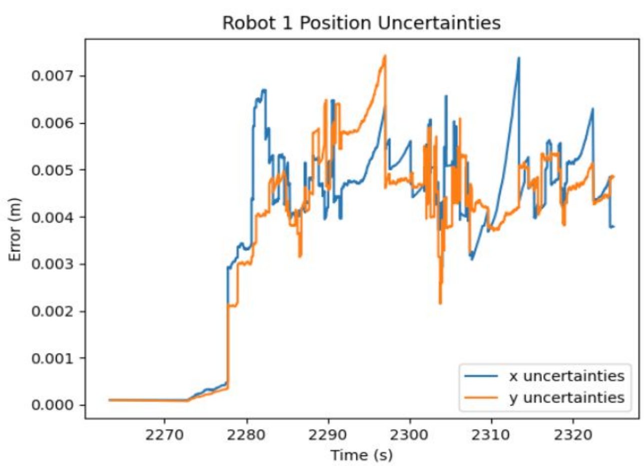

Fig. 7. Robot 1 x and y uncertainties with odometry and landmarks, but no communication.

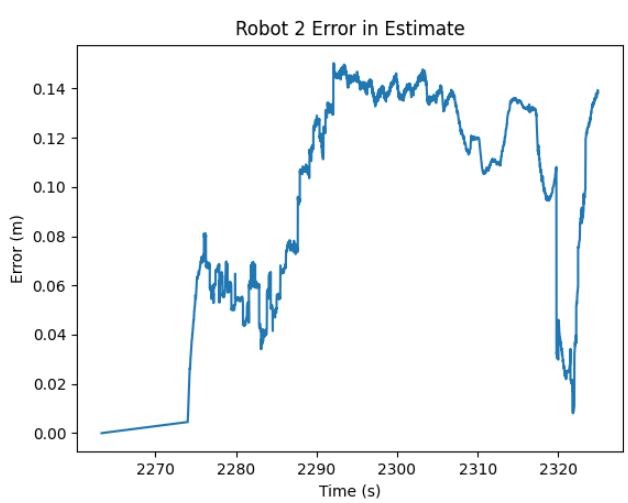

Fig. 8. Robot 2 error vs time using odometry and landmarks, but no communication.

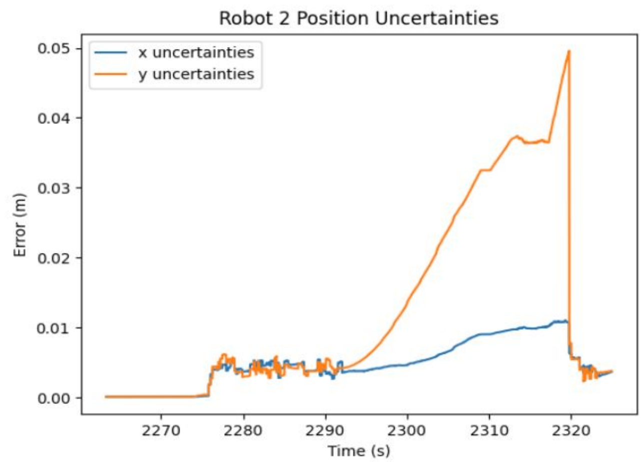

Fig. 9. Robot 2 x and y uncertainties with odometry and landmarks, but no communication.

Then, both robots were allowed to share landmark information. When one robot detected the other one, both robots shared the mean location and variance for all the landmarks they detected. Then, each robot updated their own landmark particle filters using this information. If the robot had not detected the landmark yet, it would create a new particle filter. Figures 10 through 13 display these results.

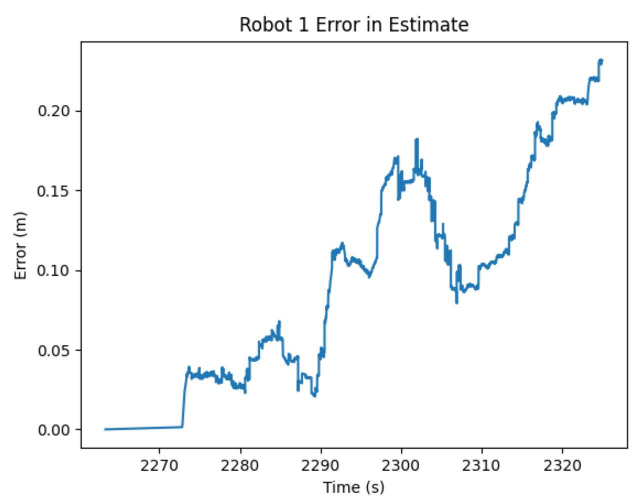

Fig. 10. Robot 1 error vs time when communicating and receiving all landmark information possible.

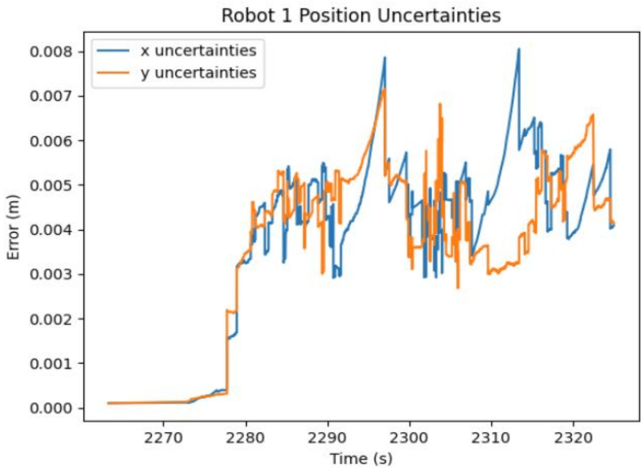

Fig. 11. Robot 1 x and y uncertainties when communicating and receiving all landmark information possible.

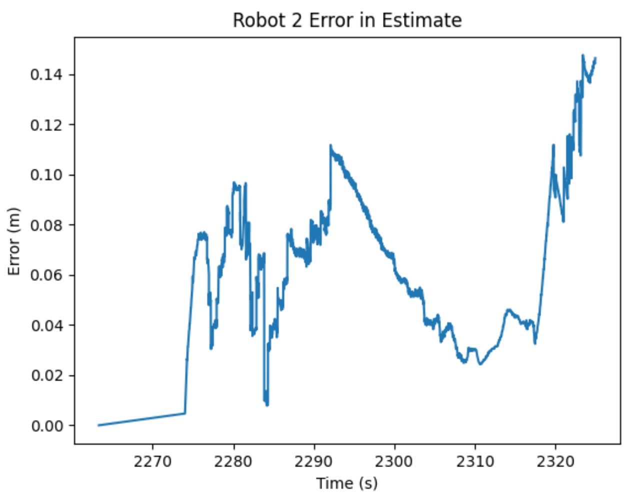

Fig. 12. Robot 2 error vs time when communicating and receiving all landmark information possible.

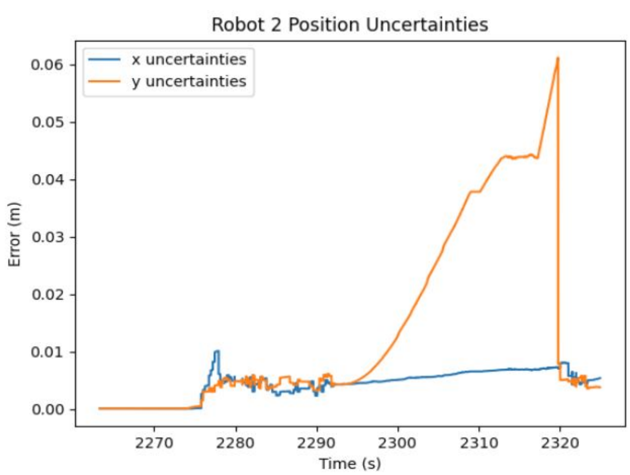

Fig. 13. Robot 2 x and y uncertainties when communicating and receiving all landmark information possible.

In the final test, when a robot detected the other one, each robot did not share all landmarks with the other one. The landmark mean and variance was only shared if the variance was below a certain threshold, or high confidence. We found that sharing landmarks that have a variance in their x or y position of less than 0.1m and less than $\frac{\pi}{10}$ (at least a 90% confidence rating) achieved good results. Figures 14 through 17 displays these results.

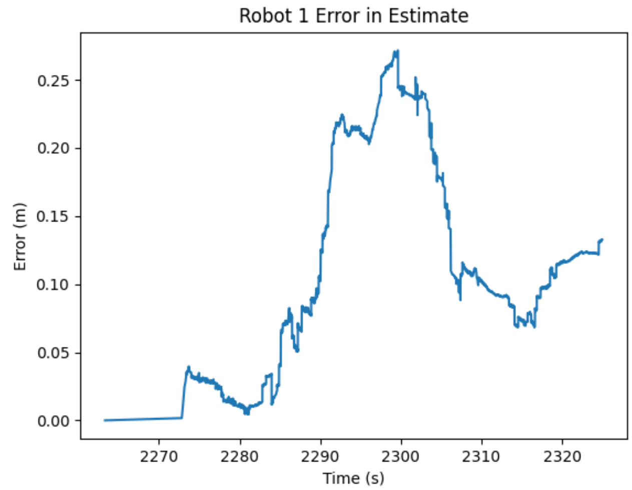

Fig. 14. Robot 1 error vs time when communicating and receiving only landmarks with a confidence rating of at least 90%.

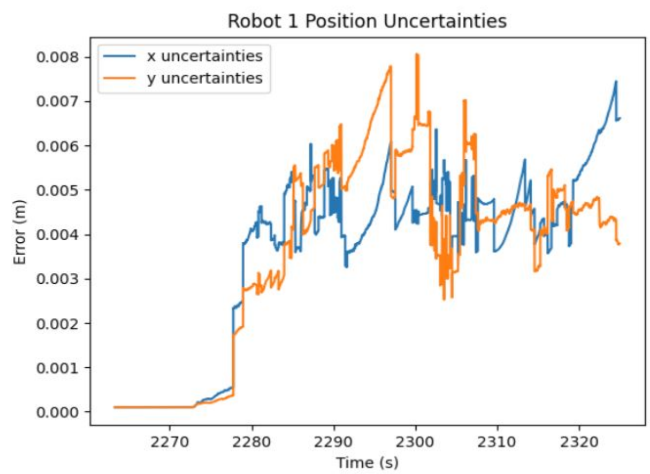

Fig. 15. Robot 1 x and y uncertainties when communicating and receiving only landmarks with a confidence rating of at least 90%.

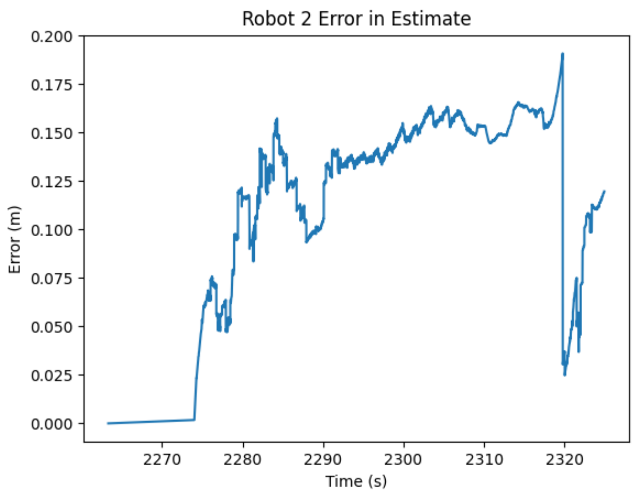

Fig. 16. Robot 2 error vs time when communicating and receiving only landmarks with a confidence rating of at least 90%.

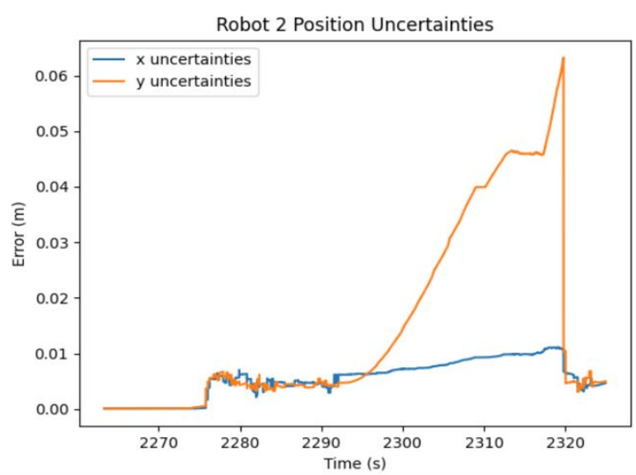

Fig. 17. Robot 2 x and y uncertainties when communicating and receiving only landmarks with a confidence rating of at least 90%.

Each test is then compared against the test where only odometry measurements were used. The reduction in error is displayed in Table I.

TABLE I
ERROR REDUCTION WITH EACH METHOD RELATIVE TO ONLY ODOMETRY

Method	R1 Error Reduction	R2 Error Reduction
Measurements, no communication	33%	28%
Communicate all info	35%	28%
Communicate confident info	65%	43%

A video discussing the project and results can be found here: https://www.youtube.com/watch?v=uGdUyuPvICg.

VI. DISCUSSION

These results demonstrate that sharing landmark locations between robots does not necessarily lead to a significant decrease in error. If landmark locations that are highly uncertain are shared to other robots, the first time another robot uses this to update its own localization, the results may be quite bad. Instead, it is more beneficial for robots to only share the landmarks that they are fairly certain of, so that other robots will be localizing themselves against good data. In Figure 1, Robot 2 is highly certain of the location of three landmarks, so it will transmit that information to Robot 1 if either robot detects each other. However, it is highly uncertain of the location of one of the landmarks. If it transmitted this information to Robot 1, Robot 1 would be attempting to localize itself based on a landmark with high variance, which may result in poor performance.

VII. CONCLUSION

Initially, we thought that the robots would perform best when they were allowed to transmit all the information that they had, and we were hoping to compare this to how well they would perform by just transmitting the most certain measurements. In practice, it was demonstrated that transmitting highly uncertain measurements can negate the benefits that the more certain measurements may provide. Thus, there is no reason to waste network bandwidth transmitting highly uncertain measurements. This means that the benefits of sharing information is still applicable in real time systems, where bandwidth constraints will reduce the amount of information that can be shared.

VIII. FUTURE WORK

If this project was continued, we would like to implement the the particle filter in [2] and compare those results to our own. Implementing this different particle filter would cause the number of particles tracking landmarks to be increased by 100 times, since each individual particle in the robot particle filter must contain its own list of landmark particles. It would be interesting to see if this increase in the number of particles leads to a significant increase in the accuracy of the robot localization.

Additionally, it would be useful to optimize our code for real-time operation and then track features obtained through images. These high density features would require more bandwidth to transmit, unlike the mean and covariance of a single landmark used in this case. Then, the bandwidth limitations could be more practically considered.

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