STUDENT SUMMER INTERNSHIP TECHNICAL REPORT

Informative Path Planning for Mapping Radiation

DOE-FIU SCIENCE & TECHNOLOGY WORKFORCE DEVELOPMENT PROGRAM

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ABSTRACT

This project consisted of making measurements of contaminated areas using portable radiation detectors and small robots. Specific tasks included learning how sensors work and are operated as well as combining data acquisition for the sensors and a robot. A methodology was designed for selecting locations for a robot to sample. Concurrently, an adaptive regression for predicting radiation distribution was implemented. The result is a radiation map of the contaminated areas.

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1. INTRODUCTION

Finding the location of radioactive sources and mapping the distribution of radioactive contamination is of great importance when dealing with emergencies or cleanup efforts. Radiation maps are used for establishing operating procedures, maintaining situational awareness, and establishing decontamination zones and safe zones. Despite the great importance of these radiation maps, the actual creation of the maps may involve hazards for anyone mapping the region, or locations that are impossible for humans to safely enter [1].

Informative path planning (IPP) is an approach for designing paths for robotic sensor platforms to efficiently gather information while attempting to reduce costs. In this case, an IPP approach was designed to maximize the information gained about the radiation distribution, while reducing the distance the robot needs to travel.

A robot equipped with a simple omnidirectional gamma ray detector was used to attempt to explore and map an unknown environment. This must be accomplished while also conforming to the robot's constraints and simultaneously achieving the best possible accuracy for the map. The work here presents a process for IPP which:

- Selects the locations where a robot should take samples
- Produces paths for the robot to use when travelling from one location to the next
- Generates a radiation map using a Gaussian process regression framework

There are existing approaches which use directional sensors [2] to gain further information about where a radiation source might be. In this work, an omnidirectional gamma sensor is utilized, meaning that the origination of the radiation when measuring at a location is not known. This greatly lowers the cost of the equipment needed, but increases the complexity of localization. The use of Gaussian process regression (GPR) and an associated utility function has been proposed by several authors [3, 4]; however, the added difficulties of navigation in an unknown environment and the rapid drop-off of the radiation signal provide additional challenges.

2. EXECUTIVE SUMMARY

This research work has been supported by the DOE-FIU Science & Technology Workforce Initiative, an innovative program developed by the US Department of Energy's Environmental Management (DOE-EM) and Florida International University's Applied Research Center (FIU-ARC). During the summer of 2018, a DOE Fellow intern Sebastian Zanlongo spent 10 weeks doing a summer internship at Aiken, SC; Savannah River National under the supervision and guidance of Dr. Timothy Aucott. The intern's project was initiated on May 29, 2018, and continued through August 2, 2018 with the objective of mapping radiation using robots. This internship was supported by the DOE EM Minority Serving Institutions Partnership Program (MSIPP).

3. RESEARCH DESCRIPTION

Provided with a set of locations where measurements have been taken, and the associated readings, a Gaussian process regression was used to estimate the underlying ground truth of the radiation. To perform the GPR, a Matérn kernel was used, which provides one of the most natural regression behaviors. When performing the regression, the expected sensor noise can be incorporated. A basic scintillator sensor model assumes a noise of $\sqrt{signal}$, and so the expected noise level was initially set at $\alpha = \sqrt{signal}$ for the diagonal of the kernel, where the diagonal is the square root of each of the measurements that were taken. The diagonal was then regularized with respect to the largest measurement taken to avoid the model from assuming all variances were due to noise.

Given a set of possible sampling locations X, the next sampling location ($x \in X$) was iteratively selected by maximizing: $x^* = max_{x \in X}\, u(x)$ where the utility function $u(x) = w \odot s$ is given by a user/application-defined weight vector $w = [a, b, c]$ and vector $s = [\mu, \sigma, \pi]$ where:

- μ is the estimated gamma counts per minute
- σ is the covariance of the joint predictive distribution at x
- π is the estimated path-length from the current robot position to the goal location, and
- $\odot$ denotes component-wise multiplication.

The gamma counts per minute are representative of the intensity of the source and rise when moving closer to the source. The path length may be considered in the event of a battery-powered robot which has a limited range.

A 2-dimensional environment populated with point sources was created. 100 simulated trials were run, where each trial had a separate distribution generated at a random location within the environment. The distribution had an intensity of between [2e3, 2e5] decays/second, and covariance ranging from [10, 30], allowing for different shapes to arise. The robot then gathered 100 samples at separate locations as dictated by the IPP algorithm. The simulated sensor model assumed a sensor efficiency of 0.3, meaning that 30% of the gamma counts are detected, and a collection time of 1 second.

Various weighting schemes were tested and compared. Quantitative evaluations often favored exploitation-heavy weighting schemes where μ was emphasized, whereas qualitative comparisons would favor exploration-biased schemes with greater weight on σ. The difference comes from operators often favoring knowing the general location of a source, rather than the exact properties of a source. Excessive weighting of the path-length π often reduced the quality of the regression as less exploration occurred; however, this may be deemed a worthwhile trade-off under certain circumstances, such as for robots with limited battery power.

Experiments were also carried out on a Turtlebot Waffle, which was equipped with a laser detection system (LDS), a light detection and ranging (LIDAR) system, and a cadmium zinc telluride (CZT) gamma ray detector.

4. RESULTS AND ANALYSIS

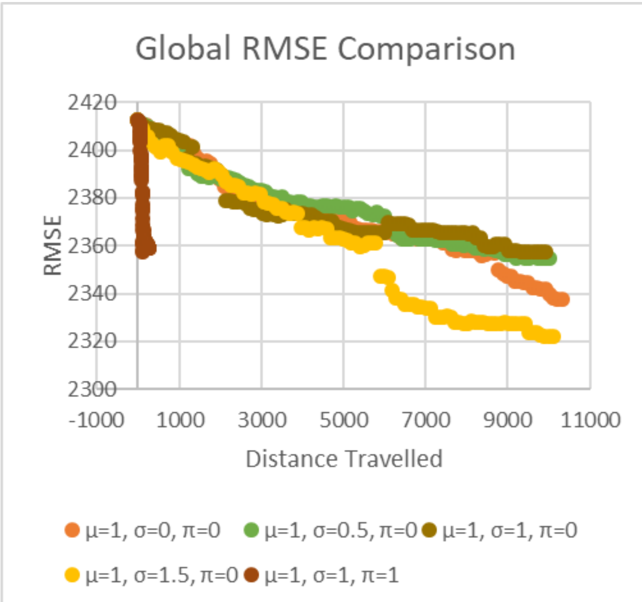

Figure 1. Global RMSE Comparison.

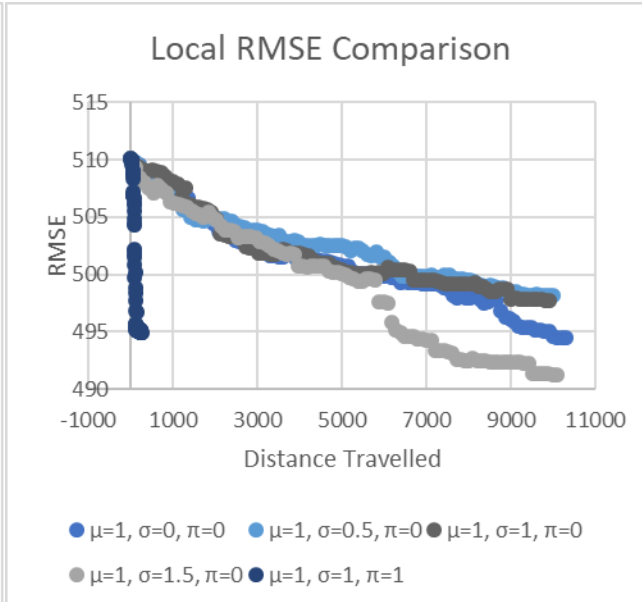

Figure 2. Local RMSE Comparison.

Select weighting schemes from the 100 trials were averaged, and can be shown in **Error! Reference source not found.** and **Error! Reference source not found.**. In **Error! Reference source not found.**, the performance of the various weighting schemes with regards to the root mean square error (RMSE) for the region immediately surrounding the point source (defined as an ellipse of size 1σ around the source) is shown. The first weighting scheme focuses on locating the point source (μ=1), yet only exhibits average performance. This is due to the optimizer getting stuck on local maxima because of not exploring enough of the environment. By increasing sigma to 0.5 or 1, more of the environment is explored but then suffer in increase in the amount of time needed to approximate the region of interest. With an exploration (σ) weight of 1.5, a good balance is found as the environment is explored, leading to low overall uncertainty and a later focus on exploring the local maxima. Interestingly, the weighting scheme of evenly balance exploitation, exploration, and distance travelled gives the most rapid minimization of RMSE. This is likely due to the distance (π) component also functioning as a multiplier for μ, as when the robot is near a maxima, it will prefer nearby measurements rather than further away exploration.

The performance seen in **Error! Reference source not found.** closely mirrors that of **Error! Reference source not found.**. This is due to the presence of a single point source, meaning that a good regression of the point source will often lead to a good regression of the overall environment.

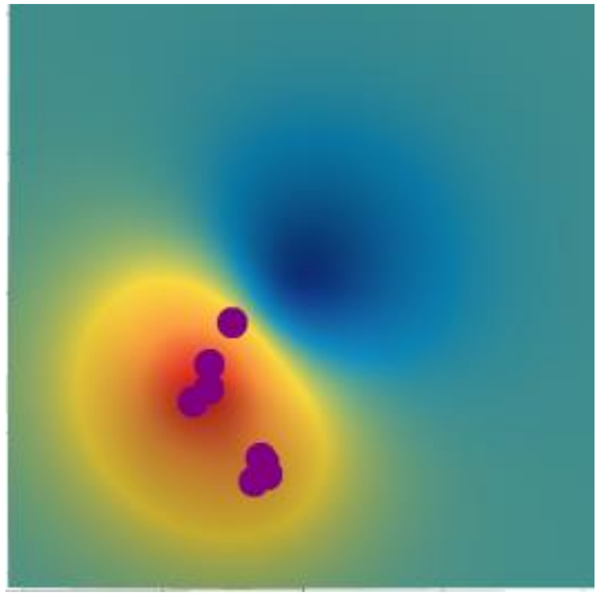

Figure 3. Reconstructed radiation distribution. Purple points correspond to locations where samples were taken. Red areas indicate higher expected radiation, and blue indicates a lower expectation.

Preliminary experiments have been conducted with a ground-robot. Data was gathered by the robot following a random trajectory, which was then used as a ground-truth to both reconstruct the radiation distribution and provide a simulated environment for a virtual robot. The reconstructed distribution (shown in Figure 3) closely aligned with the truth, where the peak of the reconstruction aligned with the actual position of the point source.

5. CONCLUSION

Early results with the informative path planning approach yielded good results in both software simulations and hardware experiments. The robot was able to localize the point sources with few samples, while further samples were used to provide further detail to the overall map. In the future, the robot's LIDAR could be used to perform simultaneous localization and mapping (SLAM) in conjunction with the radiation mapping, and to finalize integrating online IPP with the robot platform.

6. REFERENCES

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