Development of a Framework for the localization of Radioactive Sources and Evaluation Methods

Salvin George

***Abstract*—Write your abstract here.**

***Index Terms*—Write up to three keywords about your work.**

I. Introduction

It is claimed that life would not be possible without radioactivity, which is an essential component of life. Life on Earth began when naturally occurring radioactivity heated the Earth's core [1]. The science of radioactivity has come a long way since Henri Becquerel discovered it in 1896, and it is now a prerequisite for many modern technologies. Radioactive elements are used in scientific studies to determine the age of rocks and fossils. For example, in health, radioactive materials are employed in imaging and treating disease. In energy, radioactive materials are utilized in nuclear power plants and also to power spacecraft.

However, the inherent properties of radioactive materials that make them valuable also present significant challenges in their handling and security. These materials are invisible to the naked eye and can be easily concealed, making their detection and tracking a complex technological challenge. The risks associated with radioactive materials are compounded by their potential for malicious use, whether as weapons or as means of environmental contamination.

A. Motivation

The development of reliable methods for localizing radioactive sources is crucial for several reasons. First, these techniques can significantly enhance security measures by helping law enforcement and security organizations identify potential threats more quickly. Second, in industrial settings such as nuclear power plants, rapid detection of radioactive leaks is essential for maintaining operational safety and protecting both workers and the surrounding environment. The field of radioactive source localization faces several significant challenges that underscore the importance of this research. Testing with real radioactive sources is inherently difficult and potentially hazardous, necessitating the development of accurate simulation frameworks. Furthermore, the physical behavior of radiation, particularly particle attenuation and scattering, presents complex modeling challenges that affect both the simulation accuracy and the effectiveness of localization methods. While previous approaches exist, many are computationally expensive and require exhaustive area searches, making them impractical for rapid source identification. These challenges, combined with the increasing incidents of radioactive material mishandling, highlight the urgent need for more efficient and practical solutions. The development of improved localization methods could significantly enhance our ability to manage and secure radioactive materials, ultimately contributing to both public safety and environmental protection.

B. Problem Statement

The fundamental challenge in radioactive source localization lies in using sensor measurements and prior knowledge to estimate the position and intensity of unknown radiation sources within an environment. Current approaches face several key limitations: they often require exhaustive search of the entire space, struggle with sensor noise and measurement uncertainty, perform poorly in environments with limited accessibility, and suffer from high computational complexity when dealing with dynamic and large search spaces.

The core research problem encompasses three main aspects. First, the development of a physics-accurate simulation framework that can reliably model radiation behavior, including particle attenuation and scattering effects. Second, the creation of a comprehensive evaluation framework capable of assessing and comparing different localization approaches. Third, the implementation and analysis of various localization algorithms, examining their computational complexity, resource requirements, accuracy, and efficiency across different environmental conditions.

C. Proposed Approach

To address these challenges, we propose an integrated framework that combines simulation, evaluation, and algorithm implementation. The simulation component uses established radiation physics models to create realistic test scenarios, incorporating inverse square law, attenuation, and scattering effects. The evaluation framework provides quantitative metrics for assessing algorithm performance, including computational efficiency, accuracy, and robustness to noise. We implement and compare several localization methods, including rollout algorithms, entropy-based approaches, and optimization-based methods. Each method is systematically evaluated under various environmental conditions and constraints. Through this comprehensive approach, we aim to advance both the theoretical understanding and practical application of radioactive source localization.

*Submitted to the Department of Computer Science at Hochschule Bonn-Rhein-Sieg in partial fulfilment of the requirements for the degree of Master of Science in Autonomous Systems

†Prof. Dr. Sebastian Houben (Hochschule Bonn-Rhein-Sieg) and Claudia Bender (Fraunhofer FKIE)

‡Submitted in February 2025

II. Related Work

The subject of radioactive source localization is not explored as extensively as other localization problems. The main characteristic of the radioactive source search is about controlling the observer(s) position. The related works in the context of radioactive source localization have proposed different methods to solve the problem. Traditional methods relied heavily on using high number of sensors in the search and then localizing the estimated source position using least squares method [2] [3]. In the conventional methods, the observer moves through the search area following a predefined path [4]. Such a method was proposed by using uniform search [5]. Some of these autonomous methods uses triangulation-based techniques to localize the source [6] [7]. These conventional methods, while functional, face several critical limitations in efficiently localizing radioactive sources. Static sensor networks and predefined search path approaches require extensive coverage of the search area, making them more time consuming and computationally expensive.As noted in recent studies, traversal-based methods, though accurate, suffer from extremely low search efficiency [8]. These methods become highly unreliable with larger search areas as it lacks intelligence to adapt to the environment.

Bayesian estimation method is a commonly used method in the context of radioactive source localization. These methods are widely adopted due to their abiility to handle uncertainties and incorporate prior information in the localization process [8]. According to bayesian criterion, the localization of an unknown radioactive source can be determined by solving the posterior probability distribution of the source parameter vector, which can be represented through various methods including the particle filter [9] [4] [10] and other probabilistic methods. The particle filter based method, Ling et al. [10] highlight that the particle filter stands out as a practical approach that approximates the posterior distribution by maintaining and iteratively updating a set of weighted particles. At each step, the particles' weights are updated based on how likely the observed measurements are under each particle's hypothesis, and low-likelihood particles are replaced by higher-likelihood ones. As shown by Ristic et al. [9], this resampling process helps to maintain particle diversity while converging towards the most likely source parameters. They extended the particle filter approach further by introducing the information-driven strategy. Their method combines sequential bayesian estimation with Fisher information-based observer control to optimize measurement collection. Intially, when source detection confidence is low, the observer moves through the search area in following a exploration pattern. After the detection threshold is reached with sufficient probability, the observers motion and exposure time is controlled to maximize the information gain of future measurements. This method helps to guide the observer to positions that are expected to provide the most information about the source parameters. However, a key limitation fisher information emerged in study of Ristic et al. [4] is that it cannot be used before the source detection. To overcome this limitation, Ristic et al. proposed a method that uses Rényi divergence between current and predicted future posterior densities as the information gain metric. This Rényi divergence enables observer control even before the source detection, by considering the complete probability density function rather than just parameter estimates. This allows for more optimal data collection and observer control, leading to faster and more accurate source localization even before the source is detected.

Rollout algorithms, introduced by Bertsekas, represent a sequential optimization approach where variables are optimized one after another. Starting with a base policy or heuristic, rollout algorithms construct an improved policy through one-step lookahead, often yielding significantly better performance than the original heuristic while maintaining implementation simplicity [11]. Several researchers have explored rollout algorithms for source localization and path planning. Hoffmann et al. proposeda a rollout-based path planner that optimizes mobile sensor trajectories for RF source localization using look-ahead policies and cost-based optimization. While thier focus was on RF sources, the approach is generalizable to other source types, including radioactive sources due to their similar signal characteristics [12]. Tian et al. developed a multi-step look-ahead policy for UAV surveillance that incorporates a layered decision framework to balance multiple objectives including safe navigation and target tracking. Their work demonstrates the effectiveness of rollout policies in anticipating future states and making informed decisions for path planning tasks [13]. These works demonstrate the potential of rollout algorithms for efficient path planning and source localization. The success of Hoffmann's approach with RF sources and Tian's implementation for UAV surveillance suggests that adapting rollout mechanisms for radiation source localization could be particularly effective. The method's ability to improve upon base heuristics while maintaining computational efficiency makes it especially suitable for radiation scenarios where quick localization is crucial. Furthermore, the one-step lookahead policy could help navigate the complex radiation fields while accounting for particle attenuation and scattering effects.

[learning methods]

III. Background

This is an optional section in which you can introduce concepts, terms, or methods that are important for understanding your approach and that would not directly fit in Sec. IV. If you do not need this section, comment out the respective line in *report.tex*.

IV. Methodology

A. Simulation Framework

A set of simulation frameworks were investigated to select the best simulation that is available for the project. Gazebo was selected as the simulation based on its compatibility with ROS2 and the availability of the plugins that are already made available due to the familiarity of the platform. The SJTU drone system was selected as the drone model for the simulation as it was light weight and also easy to work with. A new radiation sensor plugin and radiation source plugin was developed to simulated the radiation source and the sensor. This is plugin can be easily integrated into the simulation and can be used to simulate the radiation source and the sensor.

To represent the realistic radiation behaviour, the radiation source is modelled to be a point source that emits radiation in all directions. The radiation sensor recieved and publishes the radiation data in photon count rate and this photon count rate is then subjected to attenuation due the trees and air. The attenuation due to trees is implemented using ray tracing, which helps to see of the radiation source and the sensor are in line of sight. If the trees are in the line of sight, the radiation is attenuated based on the tree type and specific attenuation factor. The tree positions are generated dynamically based on the map size but also while making sure the specific distance has been kept between the trees.

B. Evaluation Framework

A new interface for handling the simulation and experiment metrics was developed. The interface is designed with PyQt5, a Python library for creating graphical user interfaces. Two interfaces have been developed that allow one to either handle all the parameters in the workspace or visualize any number of algorithms running within the workspace.

1) Parameter Editor: The parameter editor application can be used for multiple purposes that can also be handled outside the current project. This application was developed to create a unified interface that captures all the configuration files in yaml format. To make it compatible with ROS2 packages, the interface is designed to be able to load the ROS2 package names of interest from the yaml file. This yaml file is then processed to understand which packages are to be searched for from the root of the ROS2 workspace. The found yaml files are then sorted according to the package/ workspace it was found in and the user can then select the package of interest. This will then load the yaml files and the loaded yaml files will be displayed in a tabular format. Through this interface, it is possible to remove, add, and save the changes made to the yaml files.

Another application of this interface is to find all the common parameters that are used and shared between the different algorithms. Such common parameters include parameters such as search area, source location, ros2 topic names, etc. The changes made through this section of the app are then made to all the same parameters across the project workspace. This enables the user to transition or migrate the project to a different simulation framework or configuration where the parameters are different.

2) Evaluation Visualizer: Each algorithm, upon successful completion, is saved in a JSON file format with a standardized structure. All the metrics saved in this saved file are common for all the algorithms. This was done to make the algorithms more comparable and thereby make it easier to visualize the results.

The evaluation Visualizer is an interface that is developed to visualize these results based on a set of configurations. Once the interface is opened, the user can select the input directory which contains the saved JSON files, after which the user can select a directory to save the evaluated files. Upon selecting the input directory, it will load all the JSON files in the directory, classified into the names of the algorithm. From this interface, the user can determine the number of experiments to be evaluated from the total number of runs. After running the analysis, the algorithm runs are evaluated and displayed in the next tab. Also saved locally for later visualizations. The algorithms are evaluated together based on the predefined performance metrics, and some plots that represent some other metrics from the run. It also generates a report that basically tabulates the results evaluation based on the specific algorithm.

This interface also comes with an extra tab that gives the option to generate different types of plots based on the metrics that can be selected for both the x and y-axis. Different sets of color schema also can be selected from the drop-down menus and that plot will be generated and displayed in the same window.

C. Algorithms

1) Information-Gain-based Algorithm:

2) Rollout-based Algorithm: The rollout-algorithm in dynamic optimization problems, represent a form of approximate dynamic programming that uses a base heuristic through lookahead and policy iteration [11]. A rollout algorithm simulates multiple trajectories that represent possible future states from the current state, and uses the base heuristic to evaluate these trajectories and chooses the action that maximizes the objective. This algorithm was implemented for the localization of radioactive sources, by guiding the UAV to utilize a rollout-based path planning strategy to select the next best position to move. This is algorithm borrows concepts and observations from previous works by Hoffmann et al. [12] and Tian et al. [13]

While Hoffmann et al. focused on bearing only RF emittor localization, the approach for radiation source localization needed some adaptations as it had to account for the challenges in localizing radiation sources. Where the original work focussed on optimizing bearing measurements and movement costs, our approach approach needed to account for radiation characteristics such as inverse square law decay, intensity estimation, and radiation attenuations. The intensity estimation is relevant here as the algorithm does not have prior knowledge of the source intensity. Hoffmann et al. uses a Q-value $Q(s, a)$ which is basically the expected cumulative reward of taking action a in state s and following an optimal policy thereafter. In their work, the Q-valiue is estimated by considering the cost immediate cost combining movement and measurement time, and the expected future cost again considering the movement and measurement time.

For the localization of radioactive sources, the Q-value was modified to include the continous measurement taking and

3) Inverse Square Law Optimization: The implemented localization method is based on the inverse square law for radiation intensity and serves as a deterministic baseline for comparing different radiation source search strategies. The algorithm employs a systematic spiral search pattern consisting of three concentric circles positioned at 25%, 50%, and 75% of the search area radius. This pattern begins from the center and expands outward, with the number of measurement points per circle scaling proportionally with the map size to maintain consistent coverage across different search areas.

The localization process relies on collecting radiation measurements at predefined points along this spiral trajectory. The source position estimation utilizes a weighted optimization approach incorporating the inverse square law, with higher weights assigned to stronger radiation readings to improve accuracy. To handle uncertainty in source intensity, the algorithm employs multiple optimization attempts with varying initial intensity estimates (100x, 1000x, and 10000x the maximum measured count rate) to avoid local minima. The uncertainty is further quantified through a confidence circle around the estimated source position, with its radius proportional to the standard deviation of measurements. The Nelder-Mead optimization method, constrained to the defined search area, processes these measurements to determine the most likely source position and intensity within bounded parameters.

The Nelder-Mead optimization method, constrained to the defined search area, processes these measurements to determine the most likely source position. The implementation includes real-time visualization capabilities, displaying the drone's position, measurement points color-coded by radiation intensity, true and estimated source locations, and a temporal measurement history. The system integrates with ROS2 for parameter configuration and uses the RadiationEvaluator class for performance assessment. Movement control incorporates proximity checks to ensure accurate measurements at each point, while robust error handling and cleanup procedures maintain system reliability.

This approach serves as an effective baseline for comparison due to its deterministic nature, foundation in established physics principles, reproducible behavior, and comprehensive evaluation metrics. The predefined path strategy, coupled with the inverse square law optimization, provides a methodical reference point against which more sophisticated, informed search strategies can be evaluated.

V. Evaluation

The efficiency of the simulation framework and the implemented algorithms were evaluated using a set of experiments.

VI. Conclusions

A. Summary

B. Contributions

C. Future Work

References

[1] "Doe explains...radioactivity," https://www.energy.gov/science/doe-explainsradioactivity, accessed: 2024-06-25.

[2] Y. Huang, J. Benesty, G. W. Elko, and R. M. Mersereati, "Real-time passive source localization: A practical linear-correction least-squares approach," *IEEE transactions on Speech and Audio Processing*, vol. 9, no. 8, pp. 943–956, 2001.

[3] J. W. Howse, L. O. Ticknor, and K. R. Muske, "Least squares estimation techniques for position tracking of radioactive sources," *Automatica*, vol. 37, no. 11, pp. 1727–1737, 2001.

[4] B. Ristic, M. Morelande, and A. Gunatilaka, "Information driven search for point sources of gamma radiation," *Signal Processing*, vol. 90, no. 4, pp. 1225–1239, 2010.

[5] K. Ziock and W. Goldstein, "The lost source, varying backgrounds and why bigger may not be better," in *AIP Conference Proceedings*, vol. 632, no. 1. American Institute of Physics, 2002, pp. 60–70.

[6] G. Fragkos, K. Karafasoulis, A. Kyriakis, and C. Potiriadis, "Localization of radioactive source using a network of small form factor czt sensors," 03 2020.

[7] A. H.-W. Liu, "Simulation and implementation of distributed sensor network for radiation detection," Ph.D. dissertation, California Institute of Technology, 2010.

[8] X. Hu, J. Wang, J. Huo, Y. Zhou, Y. Guo, and L. Hu, "Autonomous exploration for radioactive sources localization based on radiation field reconstruction," *Nuclear Engineering and Technology*, vol. 56, no. 4, pp. 1153–1164, 2024.

[9] B. Ristic, A. H. Gunatilaka, and M. Rutten, "An information gain driven search for a radioactive point source," *2007 10th International Conference on Information Fusion*, pp. 1–8, 2007. [Online]. Available: https://api.semanticscholar.org/CorpusID:11418497

[10] M. Ling, J. Huo, G. V. Moiseev, L. Hu, and Y. Xiao, "Multi-robot collaborative radioactive source search based on particle fusion and adaptive step size," *Annals of Nuclear Energy*, vol. 173, p. 109104, 2022.

[11] D. P. Bertsekas, "Rollout algorithms for discrete optimization: A survey," in *Handbook of combinatorial optimization*. Springer New York, 2013, vol. 5, pp. 2989–3013.

[12] F. Hoffmann, H. Schily, A. Charlish, M. Ritchie, and H. Griffiths, "A rollout based path planner for emitter localization," in *2019 22th International Conference on Information Fusion (FUSION)*, 2019, pp. 1–8.

[13] X. Tian, Y. Bar-Shalom, and K. R. Pattipati, "Multi-step look-ahead policy for autonomous cooperative surveillance by uavs in hostile environments," in *2008 47th IEEE Conference on Decision and Control*, 2008, pp. 2438–2443.

Acknowledgment

Write your acknowledgments here.

Statement of Originality

[If AI assistants have not been used, use this sentence] I, the undersigned below, declare that this work has not previously been submitted to this or any other university and that it is, unless otherwise stated, entirely my own work.

[If an AI assistant has been used, use this sentence] I, the undersigned below, declare that this work has not previously been submitted to this or any other university and that it is, unless otherwise stated, entirely my own work. The report was, in part, written with the help of the AI assistant [AI assistant name] as described in the appendix. I am aware that content generated by AI systems is no substitute for careful scientific work, which is why all AI-generated content has been critically reviewed by me, and I take full responsibility for it.

Date Signature

Appendix

Please limit the main part of the report to 20 pages (not including the references, the statement of originality, and the appendix).

In your appendix, you can add any additional details about your work, such as:

- extra results that do not necessarily belong in Sec. V
- more detailed justifications of certain algorithm design decisions
- algorithm proofs

Additionally, in the case of using AI assistants, describe in detail what content was generated using an AI assistant. In particular, name the AI assistant(s) that you used and how they were used (e.g. which prompts were used, and for which parts of the project).