Multi-Sensor Autonomous Exploration in PCV with Mobile Robot Considering Illumination Limitation

47-246781 Linfeng Sun
Supervisor: Prof. Atsushi Yamashita

This paper presents an autonomous exploration strategy for deployment in the Primary Containment Vessel (PCV) of Fukushima Daiichi Nuclear Power Station, utilizing a mobile robot equipped with range and vision sensors. The proposed method explicitly accounts for the illumination limitation inherent to the PCV environment–an aspect often overlooked in prior research. The planning process is formulated in a two-stage receding-horizon framework followed by the solution of a Fixed Start Open Traveling Salesman Problem (FSOTSP) to achieve high sensor coverage and exploration efficiency.

Key words: Multi-sensor exploration, SLAM, Fukushima Daiichi Nuclear Power Station, Decommissioning

1 Introduction

The decommissioning of the Primary Containment Vessel (PCV) is considered one of the most technically challenging aspects of the overall decommissioning process at the Fukushima Daiichi Nuclear Power Station. To support this effort, it is essential to obtain comprehensive information about the interior of the PCV, including both range and vision data, in the form of a colored map. Such a reconstructed map enables a deeper understanding of the internal situation. Specifically, visual information can assist in the detection of fuel debris, while range data provides precise localization. Furthermore, this map can serve as a foundational reference for subsequent operations, such as debris retrieval.

Due to the extremely high radiation level within the PCV, direct human entry is infeasible. As a result, mobile robots are deployed to perform data collection and inspection tasks. However, manually teleoperating these robots imposes significant cognitive load and fatigue on human operators. Moreover, teleoperation is susceptible to communication constraints such as latency, signal loss, and blackouts, especially in such complex and shielded environments. Consequently, autonomous robotic exploration has emerged as a promising alternative, capable of operating without constant human intervention and robust to communication limitations.

This task falls within the domain of autonomous exploration in unknown environments. Researchers have made significant progress in this field, primarily aiming to achieve high sensor coverage and exploration efficiency. However, most existing work focuses on coverage using single sensor modality, such as LiDAR or RGB-D camera. In contrast, relatively few studies address autonomous exploration with heterogeneous sensors–specifically, combinations of range and vision sensors that have different FoVs and distinct sensing limitations. This distinction becomes particularly critical in illumination limited environments such as inside the PCV, where cameras suffer from limited visibility due to low illumination [2], while LiDAR remains largely unaffected. As a result, the challenge of planning for effective multi-sensor coverage in such conditions remains largely underexplored.

In response to this challenge, this work proposes a novel autonomous exploration framework that explicitly addresses the challenge of multi-sensor coverage under illumination limitation. The method operates in a receding horizon scheme which consists of two stages:

- In the first stage, the system selects the next-best-view (NBV) by estimating potential information gain (IG) using range sensor modality to drive range exploration progress.
- In the second stage, the path to NBV is planned while favoring regions likely to improve vision coverage, based on a heatmap that reflects the visibility of unobserved surfaces.

By repeating these two stages in a receding horizon scheme, the robot progressively builds up both range and vision coverage. Once the range exploration is considered complete, the remaining unobserved vision targets are covered by solving a Fixed-Start Open Traveling Salesman Problem (FSOTSP), which generates an efficient final path to visit all remaining vision targets. The method utilizes a volumetric map as the planning interface, a rotating LiDAR module for SLAM and range coverage, and an omnidirectional camera module for vision coverage.

Simulation experiments are conducted in 2-D environments to demonstrate the feasibility and effectiveness of the proposed method.

The remainder of the paper is structured as follows: Section 2 provides a brief review of related work. Section 3 formulates the problem addressed in this study. Section 4 introduces the essential of proposed method. Section 5 presents simulation experiment results. Section 6 concludes the thesis.

2 Related Work

Within the field of autonomous exploration in unknown environments, a variety of approaches have been proposed. In [3], the concept of frontier–defined as regions on the boundary between free space and unexplored space was introduced for the first time in the field of autonomous exploration. Once frontiers have been detected within a particular evidence grid, the robot attempts to navigate to the nearest accessible, unvisited frontier. Repeating this process enables full exploration of the environment. Several advanced methods based on this principle, often referred to as frontier-based approaches, or Frontier Exploration Planning (FEP) according to [4], have been developed in [5], etc.

In contrast to frontier-based approaches consistently navigating the robot to frontiers, sampling-based approaches sample candidate viewpoints in the known free configuration space and select an NBV based on expected IG and travel cost. As a presentative, [1] proposed a receding horizon next-best-view planner (RH-NBVP). In this method, an RRT is grown in the current known free space to search for NBV and the branch leading to NBV is called the best branch, of which only the first edge is executed in every iteration. By repeating this process, it enables the robot to update its plan based on newly acquired information.

Several extensions of RH-NBVP have also been proposed. [4] combines the idea of FEP and RH-NBVP, with FEP as a global exploration planner and RH-NBVP for local exploration. [6] extracts frontiers and solves FSOTSP for the exploration sequence to visit all the frontiers, and the same as other RH-NBVPs, only the first edge of the exploration sequence is executed in one iteration.

For multi-sensor (range and vision) exploration, [7] and [8] generate range and vision viewpoint candidates from range and vision frontiers respectively. An NBV is selected from these candidates based on evaluation metrics considering factors such as travel cost, etc. While these methods are fundamentally frontier-based, the way they incorporate multiple sensor modalities into the decision process can inspire a natural extension of RH-NBVP by tuning the IG function to consider both range and vision IG. However, despite their elaborate design, these methods maintain a greedy nature and do not explicitly account for reduced camera visibility in low illumination environments like the interior of PCV.

Our approach is built upon RH-NBVP due to its effectiveness in online planning within unknown environments. During early stages of the exploration, we prioritize range-based NBV selection, as higher range coverage enables more informed and reliable view planning. Simultaneously, vision coverage is enhanced during path execution by biasing the planner toward visually informative regions. Finally, the remaining unobserved vision targets are covered by solving FSOTSP to generate a near-optimal path that completes the vision coverage.

-----ここから未完成-----

3 Problem Formulation

To simplify, the problem considered within this work is exploring a 2-D bounded space $V \subset \mathbb{R}^2$. To be detailed, we formulate the problem as follows.

3.1 Environment

Mapped and unmapped space by range sensor:

$V_m \cup V_{unm} = V$

$V_{occ} \cup V_{free} = V_m$

Viewed and unviewed surface by vision sensor (V_{occ} is considered as surface):

$V_v \cup V_{unv} = V_{occ}$

3.2 Sensor modality

3.2.1 Range sensor

We consider a 2-D 360-degree rotating LiDAR as range sensor. It has a maximum sensing range of r_{max}, within which it detects if there is obstacle or not along the ray, if yes, what's the distance. Ie 0/1 detection. And we map the endpoint of the ray as occupied, other points along the ray as free.

We assume the current pose of the robot is accurately estimated by processing range data using SLAM.

3.2.2 Vision sensor

To simplify, we consider a 1-D omnidirectional camera, for which we determine a maximum sensing depth of d_{max} as well as an ideal viewing distance d_{idl} manually considering low illumination. And we cast the surface within the sensing area as viewed.

3.3 Problem statement

Plan collision free trajectory $x(t)$ that in the end all the space V is mapped by range sensor and all the surface V_{occ} within V is viewed by vision sensor.

4 Proposed Method

We use a 2-D occupancy grid to represent the environment and serve as the planning interface as shown in Fig. 1.

$$Heatmap = \mathrm{Gaussian}(X,\ \mu = d_{idl},\ \sigma),$$

$$Costmap = 1 - \alpha \cdot Heatmap,$$

$$Path = \mathrm{A}^*(Occupancy\_grid,\ Costmap),$$

*1 When you write a footnote, write below a horizontal line at the bottom of the page.

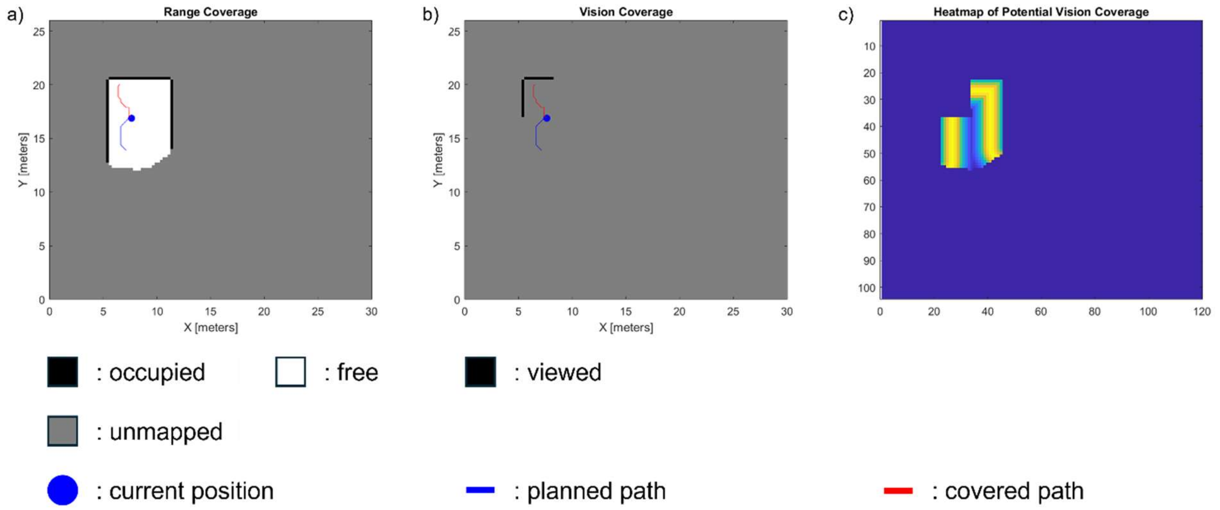


Fig . 1. Xxxx

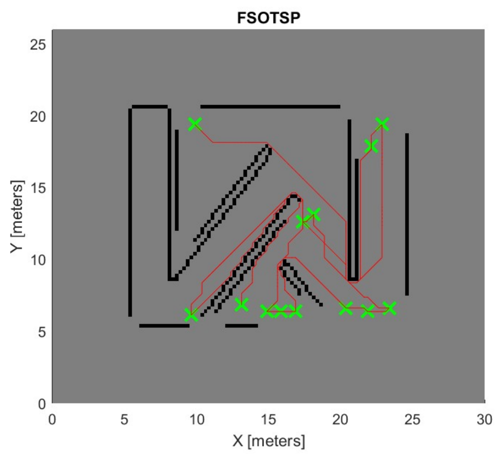
a) range coverage: xxxxxxxxxx, b) vision coverage: xxxxxxxxxxxxx, c) heatmap: xxxxxxxxxxxxxxx

Pseudo code as **Algorithm 1.**

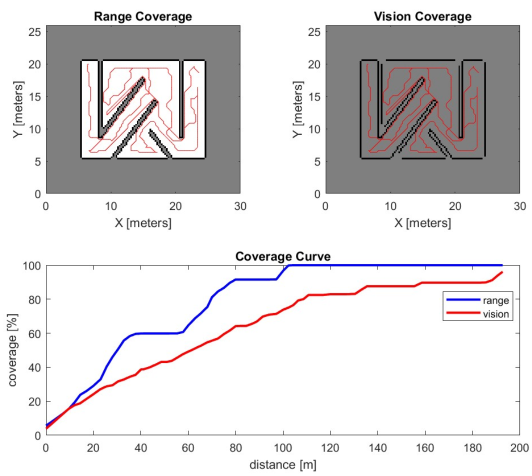
Algorithm 1 Exploration Planner

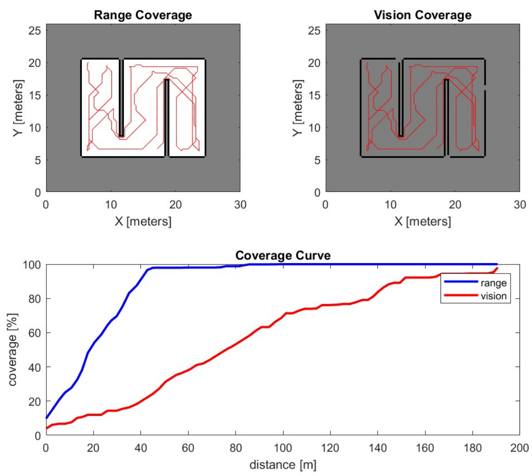
---

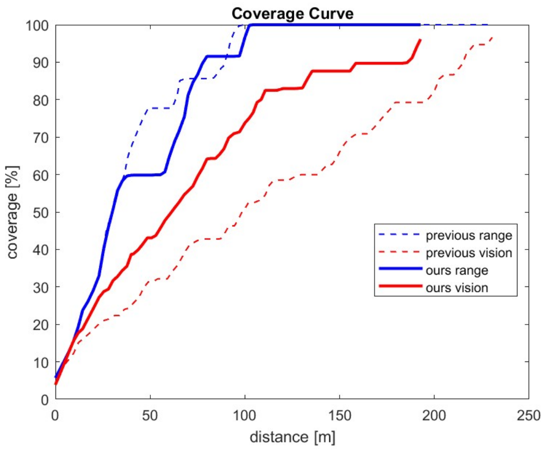
range_finish = 0
while range_finish = 0
  [*NBV*, *range_finish*] = RRT.grow(*OCC_r*, *X*)
  Heatmap = heat_caculate(*OCC_r*, *OCC_v*)
  Costmap = 1 − α · *Heatmap*
  Path = A*(occ_r, Costmap)
  RH-NBVP_EXECUTE (path)
  OCC_r = LiDAR_scan
  OCC_v = Camera_scan
end while
Heatmap = heat_caculate(*OCC_r*, *OCC_v*)
Vision_target = K-means(*Heatmap* > *threshold*)
Final_path = FSOTSP(*Vision_target*, *OCC_r*)



5 Simulation Results







6 Conclusion

Reference

1) A. Bircher, M. Kamel, K. Alexis, H. Oleynikova and R. Siegwart, "Receding Horizon "Next-Best-View" Planner for 3D Exploration," IEEE International Conference on Robotics and Automation (ICRA), pp. 1462-1468, (2016).
2) Gofuku, A., Furukawa, H., Ujita, H., "Some Investigations of Fukushima Dai-ichi Accidents from the Viewpoints of Human Factors," In: Kurosu, M. (eds) Human-Computer Interaction: Users and Contexts. HCI 2015. Lecture Notes in Computer Science, vol 9171. Springer, Cham. (2015)
3) B. Yamauchi, "A frontier-based approach for autonomous exploration," Proceedings 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation CIRA'97. 'Towards New Computational Principles for Robotics and Automation', Monterey, CA, USA, pp. 146-151, (1997)
4) M. Selin, M. Tiger, D. Duberg, F. Heintz and P. Jensfelt, "Efficient Autonomous Exploration Planning of Large-Scale 3-D Environments," in IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 1699-1706, (2019)
5) Frontier Based Exploration for Autonomous Robot.
6) Z. Meng et al., "A Two-Stage Optimized Next-View Planning Framework for 3-D Unknown Environment Exploration, and Structural Reconstruction," in IEEE Robotics and Automation Letters, vol. 2, no. 3, pp. 1680-1687, (2017)
7) Multisensor online 3D view planning for autonomous underwater exploration (2021)
8) Resilient Multi-Sensor Exploration of Multifarious Environments with a Team of Aerial Robots (2022)