A coverage path planning approach for autonomous radiation mapping with a mobile robot

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Abstract
In nuclear and radiation-related industries, it is crucial to ensure that the radiation dose exposure to the radiation worker is maintained below the permissible dose limit. A radiation map is a useful tool for visualizing the radiation distribution across the work area and for coordinating activities involving the hotspots (high radiation areas). The goal of this work was to design and implement a coverage path planning approach for autonomous radiation mapping carried out by a mobile robot. Given a 2D occupancy map, a method to generate uniformly distributed sampling points was proposed. The geometry of the region of interest, the radiation detector module, and the radiation measurement parameters were considered in formulating the sampling positions. Next, the coverage path planning planner integrates the nearest neighbor and depth-first search algorithms to create a continuous path that enables the robot to visit all the sampling points. The K-means clustering algorithm is added for systematic coverage of a large number of sampling points. The clustering provides options to partition the region of interest into smaller spaces, where the robot would perform the mapping cluster by cluster. Finally, the method of building the radiation map from the acquired data was also presented. The approach was implemented in ROS using a commercial mobile robot equipped with a Geiger-Muller detector. The performance and reliability of the proposed approach were evaluated with a series of simulations and real-world experiments. The results showed that the robot is able to perform autonomous radiation mapping at various target areas. The accuracy of the generated radiation map and the hotspots classifications were also compared and evaluated with conventional manual measurements. Overall, the theoretical frameworks and experiments have provided convincing results in the automation of hazardous work and subsequently toward improving the occupational safety of radiation workers.

Keywords
Field robotics, coverage path planning, radiation safety, radiation mapping, mobile robot navigation

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Introduction
In nuclear and radiation-related industries, radiation protection measures are crucial to ensure safe working environments. International Atomic Energy Agency guidelines have established a radiation effective dose limit of 20 mSv per year for radiation workers.¹ Radiation mapping is a...
valuable method to reveal radiation distribution and identify the positions of hotspots (high radiation areas) within the working space perimeter. This map is generated by interpolations or pattern predictions based on sparse radiation data.\(^2\) With known radiation distribution, activities around the hotspots can be efficiently coordinated, such as via path optimizations.\(^5,6\) or time regulations to comply with the permissible dose limit.

Robots equipped with radiation detectors have been utilized for radiation surveys and inspections.\(^7,8,9\) The process typically involves robots navigating within the region of interest (ROI) while acquiring data for evaluation. The navigation strategy reflects the priority of the situation. For instance, in an emergency situation, online search strategies such as reward function, field gradient, and artificial potential field (with particle filter) aim to guide the robot toward the hotspots within a short period.\(^10,11\) On the other hand, the coverage path planning (CPP) approach can be adapted for routine checks and safety assessments. CPP will enable the robot to perform detailed measurements throughout the ROI to produce detailed and comprehensive radiation maps.

There are various designs of radiation detectors, and the detection efficiency mainly relies on their types and sizes. Studies also found that the efficiency drastically drops with the increase of the distance between the source and the detector. One of the main concerns in radiation mapping is the impact of the sampling positions and its density toward the sensitivity (i.e. the resolution) of the radiation map. Improper placements of the sampling points might lead to undetected hotspots or misclassification of hotspots as clean area. In the previous works, the sampling points are typically generated at fixed distance intervals,\(^3,4,13\) or manually selected by the worker.\(^2\)

This article proposes a robust coverage radiation mapping (CRM) planner that can dynamically formulate the sampling positions by considering the radiation detector specifications and the desired radiation map sensitivity. Next, the path-planning strategy for systematic coverage of the ROIs and the method to build the radiation map and classify the area are also presented. Finally, the performance and reliability of the CRM were evaluated with a series of simulations and real-world experiments.

This article is organized as follows: The second section presents a review of related work in the field of CPP and autonomous radiation mapping with a robot; the third section describes the methodology for sampling points formulation, generation of waypoints sequence and clustering, as well as the radiation map and identification of hotspot(s). The fourth section details the experimental setup, results, and discussion. Lastly, the fifth section concludes the work and outlines future work.

### Related works

The goal of CPP is to compute a path that will pass all designated waypoints to cover the entire ROI.\(^14\) Typically, the CPP algorithm efficiency and performance are evaluated based on several criteria: the coverage ratio, path distance, completion time, energy consumption, and obstacle avoidance capability.\(^15,16\) CPP is relevant to various autonomous robotics applications such as floor cleaning,\(^19,20\) lawn mowing,\(^21\) agriculture harvesting,\(^22\) landmine detection,\(^23\) and structural inspections.\(^24\) Meanwhile, a situation that demands radiation mapping could vary from emergency response, searching for missing or orphan sources, environmental monitoring, or safety assessment of a workplace area. With respect to CPP for radiation mapping, additional factors related to radiation detection and measurement should be considered. The key factors and recent works related to the subject will be discussed in this section.

### Types of radiation detectors and mobile radiation sensing

In general, radiation detectors can be classified into three categories; the gas-filled detector, the scintillation detector, and the solid-state detector.\(^25\) Each radiation detector can be characterized by its energy resolution, detection efficiency, and dead time.\(^26\) The selection of the radiation detector depends on the requirements of the targeted application. The application should specify the type of radiation source (alpha, gamma, beta, X-ray, and neutron) and their energy levels, the intensity range, the accuracy, as well as the required data (i.e. spectral, gross count, or directional). In robotics applications, the radiation detector cost, size, weight, power consumption, and ease of installation were also considered important factors.

Several recent works on the integration of mobile robots with radiation detectors are listed in Table 1. The Geiger–Muller (GM) detector is a popular selection as it is robust, low cost, and relatively simple to implement on robots. GM output is the gross count that reflects the total intensity of the measured radiation. Meanwhile, the sodium iodide (NaI(Tl)) scintillation detector incurs a higher cost and design complexity but is capable of producing spectral data that can identify the identity of the radionuclides. In addition, a few studies proposed manipulating the physical arrangement of multiple radiation detectors to produce a directional profile from the measured data.\(^11,13,27,29\) The capabilities of gamma and Compton cameras to provide directional data to navigate the robot toward the radioactive source have also been explored.\(^30,31\) In this work, the algorithm was generalized to work with the measured gross counts obtained from any detector types. The radiation detector active area and efficiency are also considered in the computation to ensure the hotspot(s) detection accuracy.

### Radiation detection and measurement parameters

The radiation detection and measurement are influenced by several parameters, namely the counting time, the source-to-detector distance, and the attenuation of shielding
objects. This work focused on the source-to-detector distance parameter, which is governed by the inverse square law. Studies have shown that the placement and density of sampling points could determine the sensitivity of hotspot localization.39,40 Peterson et al.35 conducted field experiments with unmanned aerial vehicles (UAVs) to evaluate the performance of radioactive localization algorithms at different altitudes. They discovered lower performance at higher altitudes due to elevated Poisson noise in the measurements. Typically, the source-to-detector distance was selected based on the mapping situations and the dose interpolation or predictive techniques. In their previous work, Khuwaileh and Metwally3 sampled data at 1 m intervals in laboratories with neutron generators. The ROI is divided into three regions, and the data are collected manually by a human. Harun et al.2 also manually measured data for dose mapping in radioactive waste facilities at approximately 0.5 to 2 m intervals. Carlos et al.4 manually collected data around the perimeter of a research reactor with a fixed distance of 0.5 m along the Y-axis and a variable distance between 1 m and 0.33 m along the X-axis (depending on the area classification). Finally, Lazna et al.13 simulated data sampled along 1 m separation lines for an outdoor location with a total area of 438 m$^2$ with a mobile robot.

Meanwhile, Falkner and Marianno41 found that the speed of a moving radiation detector will influence the solid angle of the radiation detector, that is, the geometric efficiency. As the speed increases, the solid angle and the efficiency decrease. They assessed the performance and modeled the radiation detector minimum detectable amount (MDA) as a function of speed. The result is beneficial to strategize survey plans, where the speed selection can efficiently optimize the cost, time, and survey results accuracy. Exploring the same concept as in literature,41 this work utilized the radiation detector MDA to select the appropriate source-to-detector distance. Subsequently, the resolution of the radiation map is established based on the selected parameters.

### The ROI geometry and its complexity

A simple ROI polygon with no obstacles can be managed with simple back-and-forth paths or spiral paths. However, a more irregular shaped or cluttered ROI will involve obstacle avoidance and region segmentations such as cellular decompositions, rectangular, or Voronoi segmentation.42–44 The ROI geometry is typically represented in the form of a 2D or 3D map. In outdoor locations, a few studies have focused on radiation mapping with UAVs as well as cooperation between UAVs and mobile robots.13,35,45 For indoor and global positioning system (GPS)-denied locations, simultaneous localisation and mapping (SLAM) is frequently used to generate occupancy maps of the sites.11,33,34 The map indicates free and occupied areas within the ROI for path planning during the radiation survey.

As for path planning, Lazna et al.13 measured data along equally spaced parallel lines while Gao et al.46 collected data on a spiral path and proposed Peak Suppressed Particle Filter to resolve multipoint radioactive sources within the ROI. Bird et al.33 integrated frontier exploration47 to generate waypoints during the robotic inspection in an unknown location. Paulo et al.48 proposed optimizing robot trajectory with active learning and distance penalization to choose the following

### Table 1. Previous works on mobile radiation sensing (focusing on the radiation detector categories and types).

| Detector Categories | Detector types | Mobile Platform | Author(s) |
|---------------------|----------------|-----------------|-----------|
| **Gas-filled**       | GM detector   | Small differential drive mobile robot | Zakaria et al.32 |
| **Gas-filled and scintillation** | GM detector (Radeye) and scintillation probe (Thermo Fisher DP6) | Carma and Turtlebot | Bird et al.33 |
| **Gas-filled**       | GM detector (Sentinel Radeye G Dosimeter) | Not specified | Lin and Tzeng12 |
| **Scintillation**    | Three miniature Thallium-doped Cesium iodide (CsI(Tl)) detectors | RadMapper | Mascarich et al.11 |
| **Scintillation**    | Two NaI (TI) detectors | Orpheus-X3 robot | Lazna et al.13 |
| **Scintillation**    | NaI (TI) detector | Radbot | McDougall et al.34 |
| **Scintillation**    | NaI (TI) detector | Jackal (UGV) and custom hexacopter (UAV) | Peterson et al.35 |
| **Scintillation**    | Six NaI(TI) detectors and $^6$LiF panel for neutron detection | Prototype vehicle | Curtis et al.29 |
| **Scintillation**    | Lanthanum Bromide (LaBr$_3$) detector | Lynxmotion 4 wheeled differential drive chassis | Miller et al.36 |
| **Semiconductor**    | High-purity germanium (HPGe) detector | Customized Chevrolet Silverado pickup truck | Bukartas et al.37 |
| **Semiconductor**    | Cadmium zinc telluride (CZT) Compton gamma camera | Mobile robot | Lee et al.30 |
| **Others**           | Gamma camera, gamma spectrometer, dose rate detector | RICA III | Ducros and Hauser38 |
| **Others**           | Gamma camera | Miniature modular robot, marXbot | Ardiny et al.31 |
informative sampling points. Yet, the resulting paths are random and disorganized. Structured and well-organized paths will lead to a more systematic operation and reduce the possibility of spreading contamination to clean areas.

Moreover, segmentation of complex ROI would allow efficient coverage during the operation. Pinkam et al. proposed two adaptive area decomposition techniques to reduce the complexity of UAV large-scale explorations, namely recursive quadratic subdivision and Voronoi subdivision. In more general research, Goel et al. proposed rectangular boundaries within the current workspace to systematically cover an unknown environment, where the box is moved horizontally and vertically until the whole environment is covered. Miao et al. worked on the algorithm scalability where the map vertices were classified into convex or concave types. Similar to the work by Goel et al., the map will be decomposed into rectangular submaps based on the vertices criteria.

*Radiation map generation and hotspot(s) identification*

Mascarich et al. proposed constructing a grid map of the ROI with layers of believed intensity, believed gradient, intensity uncertainty, gradient uncertainty, and radiation curiosity. Upon new observation, each layer of the map was updated. Meanwhile, others built the radiation map after data collection had been completed. McDougall and Waller proposed Markov Chain Monte Carlo (MCMC) analysis to generate radiation contour throughout the ROI utilizing more sparse data points. Similarly, Kim et al. used maximum likelihood expectation maximization to reconstruct a 3D radiation image of the ROI. Lazna et al. interpolated the discrete data points from CPP with Delaunay interpolation. Pinkam et al. established hotspots boundary lines by tracking continuous contaminated cells and estimated the best fit to an ellipse shape by least-squares criterion. Bird et al. proposed an exclusion zone to prevent cross-contamination by blocking the hotspot area as a physical obstacle in the occupancy map. Both methods avoided the robot traversing across the hotspot borders to achieve time optimization and to prevent cross-contamination.

This work focused on incorporating the four key factors into the CPP approach. The radiation detectors and radiation measurement parameters will be considered in formulating the sampling positions. The proposed CRM planner will ensure coverage of the ROI and generate systematic and organized paths to reduce the risk of cross-contamination during the operation. The generated radiation map and the hotspot classification were evaluated to verify the performance and reliability of the overall approach.

**Research methodology**

In this work, the hotspot in the ROI was modeled as an isotropic point source that emits radiation in a radial pattern. The radiation intensity at the detector position, $I_i$, with source-to-detector distance, $d$, is given by

$$I_i = \left( I_s \times \frac{A \varepsilon}{4 \pi d^2} \times e^{-\mu d} \right)$$

where $I_s$ is the radiation intensity at the radioactive source position, $A$ is the detector solid angle, $\varepsilon$ is the detector efficiency, and $\mu$ is the attenuation coefficient. The approximation $e^{-\mu d} = 1$ is adopted when source-to-detector distance is less than one meter ($d < 1$ m). In addition, radioactive decay is a random event with an independent and constant rate that depends on the source of radioactivity. The probability of detecting a discrete number of events, $x$ given the mean and the variance of the distribution, $\lambda$ is modeled by the Poisson probability distribution

$$P(x, \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}$$

During radiation mapping, the robot will navigate to sampling points in the ROI and will acquire a set of observations, $Z = \{z_1, z_2, \ldots, z_n\}$. Each observation, $Z_k = \{x_k, y_k, I_k\}$, consists of the 2D sampling pose in $XY$ coordinate, $(x_k, y_k)$ and the measured radiation intensity, $I_k$ in count per second (CPS) given by

$$I_k = \frac{1}{T} \sum_{i=1}^{T} (I_i - \bar{I}_{BG})$$

where $T$ is the total counting time, $I_i$ is the total raw count, and $\bar{I}_{BG}$ is the mean of the background radiation. In normal and uncontaminated condition, the radiation intensity will fluctuate around the background radiation, $\bar{I}_{BG} \pm \sigma_{BG}$.

The flowchart of the proposed CRM planner is shown in Figure 1. The CRM planner is broken down into three subprocesses: formulation of sampling points, ROI space partition, and generation of the waypoints sequence. The sampling points are generated uniformly throughout the ROI. The spacing between the sampling points will take into account the efficiency and sensitivity of the detector module. Next, the ROI space partition provides an option to partition the ROI into smaller regions. This creates a more systematic mapping process, especially when the target area is large. Finally, the complete waypoints sequence will be generated for robot navigation during the radiation mapping process. Each of the subprocesses will be described in the following subsection.

**Formulation of sampling points for CRM**

The grid-based method provides a good base to generate uniform sampling points regardless of the shape of the ROI. Initially, the occupancy map was segmented into cells by $XY$-grids. A scale factor determines the number of horizontal and vertical neighboring pixels in the
occupancy map merged to form a cell. Given the original pixel resolution of the occupancy map, the cell height, $h$, is computed as

$$h = \frac{\text{occupancy map resolution}}{\text{scale factor}}$$  \hspace{1cm} (4)$$

Each cell in the grid is represented by a Cartesian coordinate, $(x_j^0, y_j^0)$ and an occupancy value $p$ given by

$$p(x_j^0, y_j^0) = \begin{cases} 
0, & \text{if cell is unoccupied} \\
100, & \text{if cell is occupied} \\
-1, & \text{if cell is unobserved} 
\end{cases}$$  \hspace{1cm} (5)$$

Based on the cell occupancy value, the CRM planner will identify all unoccupied cells, $U = \{u_1, u_2, \ldots, u_n\}$ where $n$ is the total number of unoccupied cells. Subsequently, the sampling points are formulated at the centroid of each unoccupied cell. With the unoccupied cell grid coordinate $(x_j^0, y_j^0)$, the cell centroid position on the original occupancy map, $(x_j, y_j)$ is computed as

$$(x_j, y_j) = (x_o + 0.5(h + x_j^0), y_o + 0.5(h + y_j^0))$$  \hspace{1cm} (6)$$

where $(x_o, y_o)$ is the occupancy map origin (obtained from the occupancy map header or map metadata). A set of sampling points is generated, $S = \{p_1, p_2, \ldots, p_n\}$ where $p_i$ is the sampling points (cell centroid position), $p_i = (x_i, y_i)$. The occupancy map segmentation and sampling points are illustrated in Figure 2.

In general, the detector MDA limits, $L_c$ and $N_D$ are expected to minimize the likelihood of false positive (no real radioactivity present) and false negative (real radioactivity present) to an error rate of below 5%.25 Considering the standard deviation of background radiation, $\sigma_{BG}$, $L_c$ and $N_D$ are computed as

$$L_c = 2.326\sigma_{BG}$$  \hspace{1cm} (7)$$

$$N_D = 2.71 + 4.65\sigma_{BG}$$  \hspace{1cm} (8)$$

These MDA limits are used to compute the sensitivity of the coverage radiation map with respect to the occupancy map cell resolution in (4). Given that the measured intensity at the sampling point is equivalent to the MDA limit ($I_k = L_c$), which indicates the presence of radioactivity), the corresponding radiation intensity, $I_{res}$, at the cell boundary can be computed as follows

$$d = 0.5 \times \sqrt{2h^2}$$  \hspace{1cm} (9)$$

$$I_{res} = L_c \times \frac{4\pi d^2}{A_i} \times e^{-\mu d}$$  \hspace{1cm} (10)$$

In other words, if a hotspot with intensity, $I_{res}$ present at the cell boundary, the expected intensity at the sampling points is approximately equal to $L_c$. As shown in

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Flowchart of the autonomous coverage radiation mapping planner (CRM planner).}
\end{figure}
Figure 3(a), this reflects a detection limit within the cell boundary, where a hotspot with an intensity equal or greater than $I_{\text{res}}$ is most likely to be detected by the sampling point regardless of its position within the cell. The significance of $I_{\text{res}}$ is further demonstrated in Figure 3(b). On the left, a hotspot with intensity greater than $I_{\text{res}}$ are detected by two sampling points with overlapping boundaries. On the right, a hotspot at the same position but with intensity lower than $I_{\text{res}}$ is not detected by any of the sampling points.

Essentially, the $I_{\text{res}}$ represent the sensitivity of the radiation map based on the background radiation, the detector efficiency, and the grid cell size. The smallest scale factor in (4) also reflects the highest radiation map sensitivity achievable with the specified detector. In addition, by controlling the cell height or the scale factor, the user would be able to customize the radiation map sensitivity according to the mapping situation and needs.

**K-means clustering for ROI space partition**

Typically, the perimeter of the target area will be cordoned when the radiation mapping is in progress. The perimeter is blocked from other activities to eliminate the risk of spreading contamination to clean areas. If the radiation mapping is expected to consume high energy and time (e.g. the ROI is large or may involve a high number of sampling points), the area could be partitioned into smaller spaces. Space partitions will allow the robot to perform mapping systematically where the clean areas can be unblocked without waiting for the whole operation to complete.

This work partitions the sampling points by implementing the K-means clustering algorithm, an unsupervised machine learning technique. K-means is chosen as it allows the user to fix the number of desired partitions or clusters, $k$ and grouped nearby sampling points based on their Euclidean distance. Initially, the K-means algorithm will randomly assign the centroids of the clusters, $c_j$ and compare their distance to each sampling point. The sampling points will be assigned into a cluster with the nearest centroid position. Next, the cluster centroids, $c_j$ are recomputed based on the mean of sampling points, $p_i$ in the respective cluster, $S_j$, given by

$$c_j = \frac{1}{|S_j|} \sum_{p_i \in S_j} p_i$$  \hspace{1cm} (11)
The K-means algorithm will iterate between sampling points cluster assignments and centroids adjustments until the centroids converge, that is, the sum of squares within the clusters are minimized. As illustrated in Figure 4(b), the output is \( k \) clusters of sampling points, \( \{S_1, S_2, \ldots, S_k\} \subseteq S \). Furthermore, the order of cluster mapping is determined to allow smooth transitions from cluster to cluster. Given the robot start position and the cluster centroids, the order of cluster is computed by the depth-first search (DFS) algorithm. As illustrated in Figure 4(c), the robot will first visit sampling points in cluster \( S_1 \), followed by clusters \( S_2, S_3, \) and \( S_4 \). The generation of sampling points, ROI space partition, and order of clusters transition are presented as pseudo-code in Algorithm 1.

**Nearest neighbor and DFS for complete waypoints sequence**

Finally, a continuous sequence of sampling points within the ROI is generated. Given the set of sampling points in the \( i \)-th cluster, \( S_i = \{p_1, p_2, \ldots, p_n\} \), nearest neighbours query is performed to identify the nearest neighbors of each sampling point.\(^{57}\) If the ROI requires no clustering, the query is performed on the original set of sampling points, \( S \). The nearest neighbors of a sampling point, \( p_i \), is defined as

\[
NN(p_i) = \{p_j \in S_i \mid \forall p_k \in S_i : d_n(p_j, p_i) \leq d_n(p_k, p_i)\}
\]

where \( d_n(p_j, p_i) \) denotes the distance between \( p_j \) and \( p_i \). The query will return a list of all sampling points with their respective nearest neighbor as follows

\[
NN(S_i) = \{p_i; p_j \mid p_i \in S_i, p_j \in S_i, p_j = NN(p_i)\}
\]

Next, the sampling points network is modelled by an undirected graph, \( G_i = (V(G_i), E(G_i)) \), where \( V(G_i) \) is the set of sampling points (i.e. the graph vertices) while \( E(G_i) \) is the set of edges that connect each sampling point to the nearest neighbor in (13). Given the start point, DFS is implemented to explore through the vertices in the graph, \( dfs(G_i, startPoint) \) to ensure that the robot will visit every sampling point. The initial robot position is assigned as the start point of the first cluster, \( clusSeq_1 \).

To create a continuous path that connects all clusters, the last sampling point of every cluster (except the final cluster), \( clusSeq_i \), is set as the start point for the following cluster, \( clusSeq_{i+1} \). Figure 5(a) illustrates the sequence

\[\text{Algorithm 1. Generation of sampling points, sampling space partition, and order of clusters transition.}\]

\[\text{Input: Occupancy map, Robot start position } p_s = (x_s, y_s)\]
\[\text{Output: Clusters of sampling points: } S_1 \text{ to } S_k \text{ where } S_i = \{p_1, p_2, \ldots, p_n\}, \text{ Order of cluster transition: } ClusSeq = \{clusSeq_1, clusSeq_2, \ldots, clusSeq_k\}\]

1: Implement grid on occupancy map
2: Get set of unoccupied cells, \( U = \{u_1, u_2, \ldots, u_n\} \)
3: Initialize set of sampling points, \( S \leftarrow \emptyset \)
4: For all unoccupied cells, \( u_i \in U \)
5: Generate sampling point, \( p_i \) at cell centroid in (6)
6: Add \( p_i \) to sampling points set, \( S \cup \{p_i\} \)
7: Partition the sampling points to \( k \) cluster with K-means clustering, \( \{S_1, S_2, \ldots, S_k\} \subseteq S \)
8: Get the K-means centroids, \( C = \{c_1, c_2, \ldots, c_k\} \)
9: Generate cluster transition order from the robot start position, \( p_s \), to all cluster centroids with Depth First Search, \( ClusSeq = \{clusSeq_1, clusSeq_2, \ldots, clusSeq_k\}\)
10: return \( S_1 \) to \( S_k \), ClusSeq
of waypoints generated within each cluster, whereas Figure 5(b) shows the continuous sequence to perform the radiation mapping from the initial robot position in (b).

Algorithm 2. Generation of waypoints sequence for coverage radiation mapping.

| Input: Sampling points clusters: $S_1$ to $S_k$ where $S_i = \{p_1, p_2, \ldots, p_n\}$, Sequence of cluster transition: ClusSeq |
| Output: Waypoints sequence; $W_p$ |
|---|
| 1: Get cluster sequence, ClusSeq |
| 2: Assign robot initial position as start point, $startPoint = p_i$ |
| 3: For cluster in cluster sequence, $clusSeq_i$, where $clusSeq_i \in ClusSeq$ |
| 4: Get sampling points in current cluster sequence, $S_i$ |
| 5: Insert start point as the first sampling point in current cluster, $S_i \cup \{p_i\} = S_i \cup \{(1, p_i)\}$ |
| 6: Get the two nearest neighbours for each of the sampling points, $NN(S_i) = \{p_i, p_j | p_i \in S_i, p_j \in S_i, p_j = NN(p_i)\}$ |
| 7: Construct graph to model $S_i$ network, $G_i = (V(G_i), E(G_i))$ |
| 8: Arrange sampling points traversal sequence, $S_i = dfs_{preorder}(G_i, startPoint)$ |
| 9: Assign last point in the sequence as the start point for next cluster |
| 10: Create complete waypoint of the ROI, $W_p = \bigcup_{i=1}^{k} S_i$ |
| 11: return $W_p$ |

Results and discussion

A series of simulations and real-world experiments were conducted to evaluate the functionality and the performance of CRM. In this section, the experimental setup and the obtained results will be discussed.

Setup of robot platform and radioactive sources

A dedicated ROS package, rad_mapper, was developed to implement the CRM planner (Algorithms 1 and 2) as shown in Figure 6. The algorithm code was written as an ROS service, whereas amcl and move_base packages were integrated for robot localization on the occupancy map and navigation. The rad_mapper was run on Turtlebot with GM detector module developed in the previous work. GM is a gas-filled tube type radiation detector which generates voltage pulses as it interacts with radiation. The physical setup of the robot has also been presented in Figure 6.
The real-world experiments were conducted in indoor environments. Prior to the experiments, the background radiation \( (I_{BG} \sigma_{BG}) \) without the presence of radioactive sources was measured at 1.86 ± 0.14 CPS. A combination of low-activity radioactive sources ranging from 50 kBq to 100 kBq was used to run the real-world experiments. The reference (true) value for hotspot radiation intensity was approximately 5000 CPS, acquired from high-purity germanium (HPGe) gamma spectrometry system with a gamma efficiency of 25%.

**Evaluation of the sampling points formulation**

First, the sampling point formulation with different grid scale factors is evaluated. Figure 7 shows the ROI and the 2D occupancy map of approximately 3.5 m × 7 m dimension. Figure 8 shows the resulting grids for scale factors of 5, 4, 3, and 2, where the sampling points are generated at the centroid of each unoccupied cell. Then, based on the GM technical specification, the \( I_{res} \) for each scale factor is computed in (10) and summarized in Table 2. The results clearly show that small-scale factors will create dense sampling points and increase the resolution of the radiation map.

As the robot will measure all sampling points, the trade-offs for small-scale factors are the completion time and the energy consumption of the robot. The scale factor should be selected depending on the desired radiation map resolution. For instance, if the situation deals with high-intensity radioactive source(s), a higher scale factor is sufficient to detect the hotspots. On the other hand, operations for low-intensity radioactive source(s) may require smaller scale factors. In both cases, the proposed approach could be employed to choose the appropriate configurations to ensure the accuracy of the hotspot’s detection.

**Evaluation of the CPP**

Next, the functionality of the CPP path planning was simulated on 10 × 10 grid cells ROIs with various configurations of obstacles. The simulation results are presented in Table 3. Column 2 shows the sampling points generated for every unoccupied cell of each workspace. Column 3
Table 2. The radiation map parameters and the map resolution.

| Scale factor | Total sampling points | Cell height, $h$ (m) | Distance, $d$ (m) | Map resolution, $I_{res}$ |
|--------------|-----------------------|----------------------|------------------|--------------------------|
| 5            | 24                    | 0.25                 | 0.176            | 897                      |
| 4            | 75                    | 0.20                 | 0.140            | 568                      |
| 3            | 166                   | 0.15                 | 0.100            | 290                      |
| 2            | 495                   | 0.10                 | 0.070            | 142                      |

Figure 8. Grid and cell size comparison for scale factors 5, 4, 3, and 2 (from left to right).

Table 3. Simulation of the proposed coverage path planning.

| Workspace | Formulated sampling points | Workspace partition with K-means partition | Waypoints sequence with no partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) | Waypoints sequence with K-means partition (Green: start, Red: end) |

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presents the results of K-means clustering ($k = 4$), where the colors of the sampling points represent their clusters. Columns 4 and 5 compare the waypoints sequences with no partitions and with K-means space partitions. The results showed that the implementation of nearest neighbors and DFS enabled the robot to visit every sampling point in the workspace. Moreover, K-means clustering provided alternatives to divide the workspace into clusters and the robot could systematically perform the radiation mapping according to the cluster sequence.

Figure 9. Comparison between (a) RViz mapping trajectory without area partition and (b) with area partition. (The difference in green cells’ color tones in (a) has no significant effect to the results and can be neglected).
Next, the CPP approach is evaluated in real-world experiments where the robot was deployed to perform the autonomous radiation mapping on two ROIs. The dimension of ROI1 is 8.4 m x 9.7 m, whereas the dimension of ROI2 is 5.95 m x 4.9 m. Scale factor 7 is selected, where the ROIs were segmented into 0.35 m x 0.35 m cells. Figure 9 compares the trajectories taken by the robot with no partitions and with K-means space partitions on ROI1. During the mapping, if the target pose was blocked by dynamic obstacles and no alternative pose was available, the sampling point was skipped, and the robot proceeded to the next waypoint.

Both approaches were repeated five times to evaluate the differences in terms of the path length, completion time, coverage percentage, and error of sampling positions. The results are presented in Table 4. The average path length and completion time for no space partition were consistently less than the K-means partition. This was mainly due to the back-and-forth movement within the smaller partitions. The completion time could be estimated by using two factors; the total measurement time (the number of sampling points multiplied by the counting time) and the traveling time (robot average velocity multiplied by the total path distance). The displacement error between the target sampling pose and the true sampling pose is visually presented in Figure 10.

In these CPP experiments, the results have shown that the robot was able to generate the sampling points for the intended ROIs and generate paths to cover the sampling points. The real-world evaluation proved that both approaches have successfully covered 100% of the sampling points. Although the K-means clustering consistently produces longer path lengths and completion time, it provides a good alternative to partition the ROI into smaller spaces. This option is recommended when the ROI size is large, or the operation requires a small-scale factor and involves a high number of sampling points (as discussed in section “Evaluation of the sampling points formulation”) which is time and energy consuming. For example, the K-means clustering can help to systematically strategized the overall operation. The clustering allows consecutive procedure such as decontamination operation on completed clusters. It also creates the opportunity for parallel mapping by multiple robots in the future.

**Evaluation of the radiation map and hotspot(s) localization**

During the real-world experiments, radioactive sources were placed at selected locations in the environment as shown in Figure 11. In the first experiment, the scale factor 7 was selected with 0.35 m x 0.35 m cells dimension and \( I_{res} \) of 1649 CPS. The counting time at each of the sampling points was 5s.

The set of observations acquired by the robot is plotted in Figure 12(a), while the interpolated data and the radiation map are shown in Figure 12(b) and 12(c). Figure 13 shows the radiation map overlayed on the occupancy map to visualize the data 2D positions. The hotspots were defined at locations where the total count was greater than 20 (twice the measured background, \( I_{BG} \)). The boundary that separated the clean and hotspot areas has been marked with the black contour line. As shown in Figure 13, the hotspot positions were consistent with the positions of the radioactive sources in Figure 11.

To validate the radiation map, comparison was carried out between the interpolated data and manually sampled data. To maintain the consistency of the spatial position and radiation measurement accuracy, the same mobile robot and radiation detector module (TurtleBot with GM) in Figure 6 was used to collect the data manually at the prescribed location. First, the CPP data were sampled at a grid dimension of 0.15 m x 0.15 m (scale factor 3), with a total of

![Figure 10. Sampling point displacement error.](image)

**Table 4. Real-world evaluation of the proposed coverage path planning.**

| ROI location | CRM planner | Total sampling points | Path length (m) | Completion time (mins) | Coverage | Average displacement error (m) |
|--------------|-------------|-----------------------|-----------------|------------------------|----------|-----------------------------|
| 1            | No partition | 37                    | 11.75           | 3.7                    | 100%     | 0.103 ± 0.021               |
|              | K-means partition | 37                    | 17.44           | 4.07                   | 100%     | 0.105 ± 0.028               |
| 2            | No partition | 228                   | 72.72           | 23.3                   | 100%     | 0.103 ± 0.020               |
|              | K-means partition | 228                   | 76.13           | 26.6                   | 100%     | 0.103 ± 0.026               |

ROI: region of interest.
155 sampling points, as shown in Figure 14(a). The data set was interpolated into 100 × 100 mesh grid size in Figure 14(b). Next, data were sampled at higher grid resolution with a cell dimension of 0.10 m × 0.10 m (scale factor 2) and a total of 495 sampling points in Figure 14(c). All data sets indicate elevated radiation intensity around the true location of the radioactive source. Finally, individual sampling points classification (clean or hot spots) at the same overlapping positions from Figure 14(b) and 14(c) were compared and 85% were found to be similar.

In addition, the comparison was carried out using with manually measured data at scattered sampling points as indicated in Figure 15. The manual sampling points were chosen at the locations that were not directly measured in the CPP sampling points and covered both clean and contaminated spaces. The radiation intensity (total count) and classification from the radiation map and manual measurement were compared and presented in Table 5.

Of the 19 sampling points, three results were found to be inconsistent where the radiation map hotspots were classified as clean with the manual measurement. In particular, the sampling points (9, 12, and 16) were located near the boundary line. At these locations, the measured value was dominated by Poisson noise and mainly fluctuated around the background value, $I_{BG}$. Notably, it was safer to define these points as hotspots as part of occupational safety precautions. In terms of optimizing the safety of radiation workers, the generated radiation map could be utilized to coordinate safe routes and time duration during any activity within the ROI. Thus, radiation exposure could be efficiently reduced and minimized in accordance with As Low As Reasonable Achievable (ALARA) practice.

In this series of experiments, the capability and functionality of the proposed approach with a low-cost GM tube detector have been explored. GM-based radiation survey instruments are commonly available in any radiation-
related facilities to comply with safety regulations. Successful implementation of our CRM approach can provide a cost-effective solution that can be adopted for regular safety inspection of nuclear and radiation facilities. A detector with higher efficiency can be used as the front-end sensor to improve or increase the sensitivity of the system.

Conclusion

In this article, a CPP approach for autonomous radiation mapping with a mobile robot was proposed. First, the grid-based method was adapted to generate uniformly distributed sampling points throughout the ROI. Given the grid cell size and the detector MDA limit, the sensitivity of the radiation map can be computed. This enables the user to customize the radiation map sensitivity according to the mapping needs and situations. Next, the K-means clustering algorithm was implemented to provide options to partition the ROI into smaller spaces for a more systematic coverage. Integration of nearest neighbor and DFS were adapted to generate a continuous waypoints sequence for robot navigation during the radiation mapping. Finally, the measured data were interpolated onto a dense mesh grid with IDW interpolation to generate the radiation map. Contour lines were plotted on the map to indicate the borders between clean and hotspot(s) areas.

The results showed that the approach had enabled the robot to perform autonomous radiation measurements at the formulated sampling positions. In addition, the average path length and completion time for no space partition were consistently less than the K-means partition due to the back-and-forth movement within the smaller partitions. The generated radiation map was compared and evaluated with manually measured data. Overall, this approach provided an autonomous radiation mapping for safety in radiation facilities or related infrastructures.
In the future, this work will be extended for exploration of unknown environments as well as auto-tuning of the counting time parameter, which was done manually in the current work. The K-means clustering also provides the opportunity for multi-robot radiation mapping operation. The ability of other detectors, such as pin-diode detectors, which can be packaged onto a smaller robot (e.g. small UAV), will be explored for the application of autonomous radiation mapping.

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Table 5. Comparison between radiation map and manual measurement point classification.

| Test point | Radiation map (total count) | Classification | Measured data (total count) | Classification | Results |
|------------|-----------------------------|----------------|-----------------------------|----------------|---------|
| 1          | 24.9                        | Clean          | 24.0                        | Clean          | ✓       |
| 2          | 33.97                       | Hotspot        | 34.0                        | Hotspot        | ✓       |
| 3          | 41.2                        | Hotspot        | 37.2                        | Hotspot        | ✓       |
| 4          | 32.2                        | Hotspot        | 32.2                        | Hotspot        | ✓       |
| 5          | 19.0                        | Clean          | 24.5                        | Clean          | ✓       |
| 6          | 15.3                        | Clean          | 17.0                        | Clean          | ✓       |
| 7          | 11.95                       | Clean          | 15.7                        | Clean          | ✓       |
| 8          | 26.1                        | Hotspot        | 29.2                        | Hotspot        | ✓       |
| 9          | 28.3                        | Hotspot        | 23.2                        | Clean          | ✓       |
| 10         | 7.96                        | Clean          | 13.6                        | Clean          | ✓       |
| 11         | 8.69                        | Clean          | 15.0                        | Clean          | ✓       |
| 12         | 26.1                        | Hotspot        | 21.4                        | Clean          | ✓       |
| 13         | 22.18                       | Clean          | 18.8                        | Clean          | ✓       |
| 14         | 11.8                        | Clean          | 15.3                        | Clean          | ✓       |
| 15         | 42.4                        | Hotspot        | 31.2                        | Hotspot        | ✓       |
| 16         | 31.4                        | Hotspot        | 22.0                        | Clean          | ✓       |
| 17         | 17.66                       | Clean          | 12.1                        | Clean          | ✓       |
| 18         | 19.2                        | Clean          | 11.6                        | Clean          | ✓       |
| 19         | 16.9                        | Clean          | 11.5                        | Clean          | ✓       |

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