Robotic Radiation Mapping from Sparse Data

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Abstract

Radiation maps show how a radiation field varies spatially over an area, usually by overlaying radiation intensity readings on a physical map as isobars. These maps have the potential to help significantly reduce exposure to ionizing radiation in industrial and emergency scenarios by identifying those regions where the radiation intensities are critically high in a format understandable to people from a wide range of technical backgrounds. In this work, a procedure for generating these maps using data acquired by sensors mounted on mobile robots from a limited portion of the area being mapped is introduced and tested in a simulation study. The results show that the proposed method is effective at generating radiation maps from sparse data.

Keywords: Radiation Modeling, Radiation Maps, Mobile Robotics, Markov-Chain Monte Carlo (MCMC) Study, Bayesian Inference, Forward Monte Carlo (FMC) Analysis

1 INTRODUCTION

There are a number of different techniques in the literature for generating radiation maps, but the general idea for all of them is to conduct methodical radiation sensor surveys of the zone under-study, taking radiation intensity readings at an appropriate interval through the entire area so that the end-result is of sufficient fidelity for the application at hand. The differences then between the methods are the manners in which the complete sensor survey is performed.

In situations where it is known ahead of time that a radiation map will be needed, the simplest approach is to use a network of static sensors, placed prior to the exposure occurring, to conduct the radiation sensor survey required for the map [1–3]. A radiation map is simply generated by taking readings from all the nodes in the static sensor net and transferring them to a physical map. This method is relatively easy and inexpensive to deploy, but offers no solution to generating maps for an area that has not been identified in advance. For these situations, where a radiation map is required for an area that has not been equipped with a static sensor net ahead of time, it is necessary to develop a strategy for taking the necessary radiation readings by manually positioning a sensor throughout the area under study "on-demand".

The literature contains several strategies for completing the above surveys dynamically. In the most ideal circumstances, when the radiation field is known to be weak and stable, then the survey can be conducted by operators with hand-held sensors [4, 5]. For unknown sources or environments, it is not desirable to risk human exposure to unknown radiation fields. In these cases, an alternative is to use mobile robots to transport the radiation sensors to conduct the radiation survey.

To this end, two algorithms have been proposed for controlling the mobile robot's path while completing the search in [5, 6]. In the first, a sequential-based Bayesian method, the robot simply moves through each cell one-by-one in an arbitrary order, staying positioned in each cell until the local uncertainty in the radiation measurement is beneath an assigned threshold, since as long as the strength of source is not particularly transient, the confidence in the inferred mean of the signal will increase. The alternative procedure, a gradient-based Bayesian method, modifies the exploration routine of the robot slightly by encouraging the robot to visit areas with the highest uncertainty (variance) as opposed to just progressing through the cells sequentially. These controls are based on entropy inspired density functions or other optimization based techniques [6]. At the end of each update, the controller evaluates the uncertainty in the nine adjacent cells and the robot moves to the one with the highest uncertainty next.

Regardless of the techniques used to acquire the sensor readings, the entire task becomes increasingly complex in scenarios that deviate from these ideal conditions. In these cases, it is impossible to move a sensor throughout the entire area under study due to physical obstacles or other impediments. To generate radiation maps of such areas requires the application of predictive modeling, in combination with measured data, to approximate the radiation field where direct sampling is infeasible.

In this work, utilizing a simulation study, the effectiveness of a multi-stage procedure for generating radiation maps for an area using sensor readings acquired via a mobile robot is investigated. In this method, the sensor readings acquired from the passable regions in the area being studied are used to calibrate an appropriately selected model so that it best matches the real-life scenario

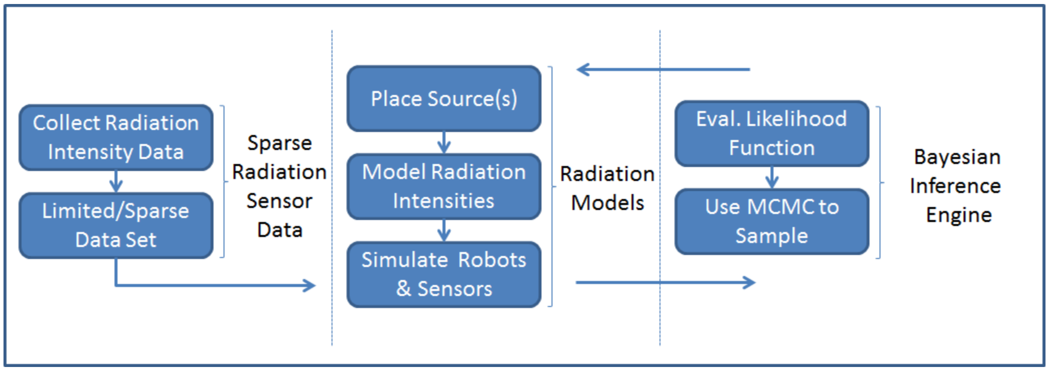


Figure 1: Functional Overview of Proposed Approach.

using Bayesian inference techniques to help account for positional error in the mobile robot survey and the discrete nature of the radiation intensity measurements. Once the locations and intensities of the radiation sources which are most likely to match the measured data have been determined, Monte Carlo analysis is used to fill in the areas on the radiation map corresponding to the portions where it was impossible to position a sensor. In the following sections, an overview of the integrated approach is presented and then its effectiveness is studied through a simulation study.

2 Models and Methods

The proposed strategy was examined in a four-step simulation study illustrated in Figure 1. First, a radiation intensity model was developed to model the radiation intensities for the complete area given sources of known position and intensity. Next, a radiation sensor model was created to simulate sensor readings taken from a relatively small section of the area taking into consideration both the position error from the model robot and the discrete nature of the radiation field intensity. The readings from the simulated sensors alone were then used in a Markov Chain Monte Carlo (MCMC) [7] inference study to estimate the locations and intensity of the sources. Finally, Forward Monte Carlo (FMC) analysis was done using the posterior distributions from the MCMC study to generate the probabilistic radiation map.

2.1 Radiation Model

For the purposes of this preliminary study, the radiation model for each source used in the study was defined by three parameters: one representing the radiation intensity and two to characterize the position where the mobile robot took the reading. The mean radiation R_p at point $P(x,y)$ resulting from j independent point sources was then defined as:

$$R_p = \sum_{i=1}^{j} R_i \tag{1}$$

where the contribution from the ith source R_i is calculated by applying the inverse square law [8]:

$$R_i = M_i * [(P_x - Ps_{xi})^2 + (P_y - Ps_{yi})^2]^{0.5} \tag{2}$$

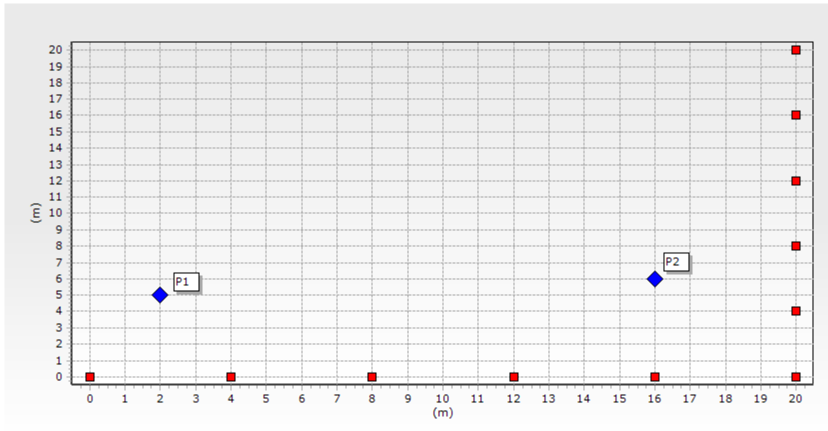


Figure 2: Layout Showing the Position of the Sources (Diamonds) and Measurements Taken (Squares).

where M_i is the source intensity, and P_x, P_y, Ps_x, and Ps_y are the x and y coordinates of the ith measurement and source locations, respectively.

2.2 Mobile Robot Model

A simple mobile robot model was used to account for the difference between where the robot is commanded to go and take radiation samples for each location and where it actually ends up. These deviations are later treated as inferred parameters in the source inference stage. It is up to the designer's discretion whether or not each commanded position should have its own error, or whether or not it is most likely that the error will be similar for each point. Furthermore, normal or eccentric error models can be used whether they are proportional to the distance traveled from the last sampling point or not. In this work, the error function used for each point was identical and uniformly distributed at +/- 0.5% of the total width of the area being studied.

2.3 Radiation Sensor Model

The radiation sensor model is based on sampling from the Poisson distribution as in [6] where the intensity measured at point $P(x, y)$, R_{mp}, is given by:

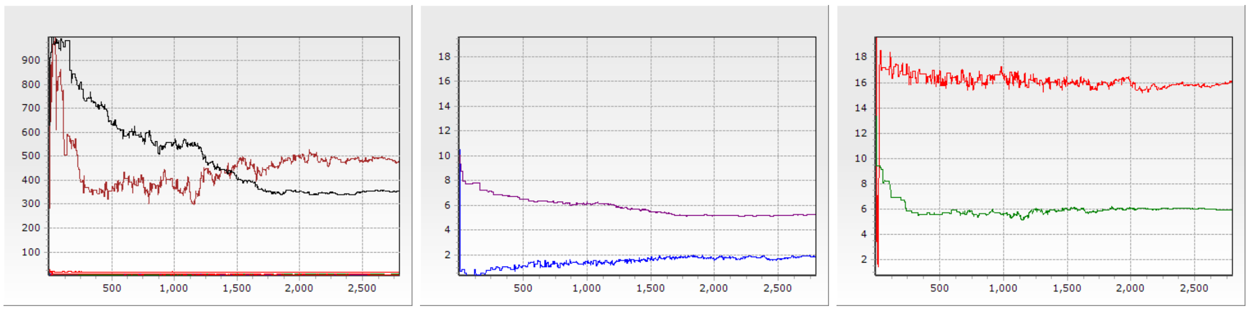
$$R_{mp} = Pois(\lambda) \tag{3}$$

where $Pois$ is the Poisson function as described in [9] and λ is the count rate corresponding to the Radiation intensity for point $P(x, y)$ calculated in Eq. (1).

2.4 Inference using Markov Chain Monte Carlo Techniques

The MCMC [7] study is designed so that the parameters being inferred are the locations and intensities of all the sources, and are performed using uninformative priors and normal error models. The likelihood function, LF, sampled in the study for a given proposal is:

$$LF = \sum_{i=1}^{m} (R_{p,pi} - R_{mp,i})^2 \tag{4}$$



(a) Intensity of Sources - Chains (b) Position (X & Y) for Source 1 - Chains (c) Position (X & Y) for Source 2 - Chains

Figure 3: Markov Chain Monte Carlo Analysis - Posterior Chains.

where m is the number of readings, $R_{p,pi}$ is the radiation intensity predicted for a given proposal at the ith point from Eq. (1), and $R_{mp,i}$ is the sensor reading for the ith point from Eq. (3).

2.5 Radiation Map Generation using Forward Monte Carlo Analysis

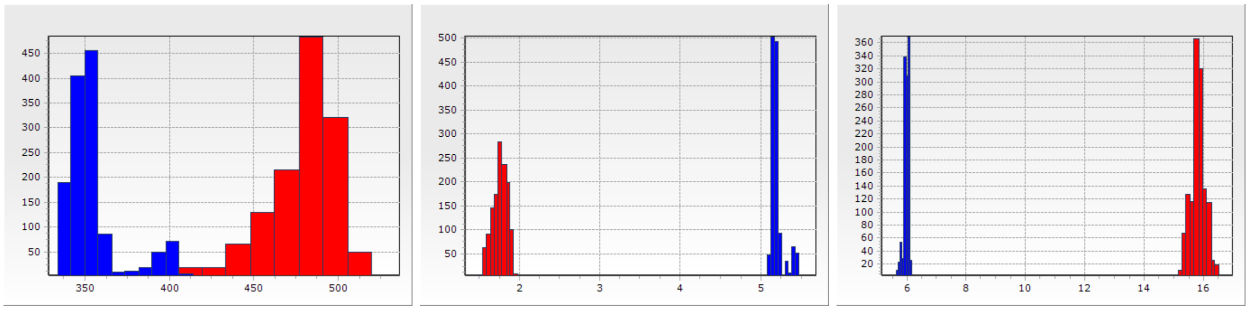
Once the chains of the MCMC analysis have converged, the resulting marginal distributions for each parameter from every source are used to generate the radiation map. A sufficient number of iterations should be considered, the optimum number depending of course on the nature of the posterior distributions for each parameter inferred during the MCMC study.

3 Simulations and Results

To test the preliminary effectiveness of the mobile-robot assisted radiation map generation scheme, a 20 m x 20 m area exposed to two radiation sources was modeled. The proposed algorithm was then used to generate radiation maps and the results were compared to the modeled area. As illustrated in Figure 2, sources were placed at positions $P_1 = (2, 5)$, and $P_2 = (16, 6)$ with differing intensities of $I_1 = 350$ and $I_2 = 450$ counts per minute (CPM). The simulated mobile robot was commanded to take five measurement samples along the leftmost and bottom edges at intervals of 4 metres as shown in Figure 2.

The radiation mapping strategy proposed here was successful in the simulation study. Figures 3a, 3b, and 3c show the resulting chains from the MCMC analysis for the posterior values of the intensities and positions for each source. For each parameters, the MCMC algorithm was able to achieve convergence after around 2,000 iterations.

Plotting the distributions of the posteriors of each parameter from the converged sections of each chain (when the number of iterations is greater than 2,000) shows that the converged chains are distributed log-normally around the expected values (i.e., those "real" values from the radiation model simulating the real-environment) as illustrated in Figures 4a, 4b, and 4c. Since the distributions of the frequencies for the converged portions of the chains for each parameter were centered on their true values, the developed method was able to accurately generate a radiation map (see Figure 5) for the whole area in spite of the fact that samples were only taken from two edges and



(a) Posterior Distributions for Intensities for Both Sources

(b) Posterior Distributions for Pos X and Pos Y for Source 1

(c) Posterior Distributions for Pos X and Pos Y for Source 2

Figure 4: Markov Chain Monte Carlo Analysis - Posterior Distributions of Inferred Parameters.

positional errors of the mobile robot and errors in the radiation sensor readings were considered.

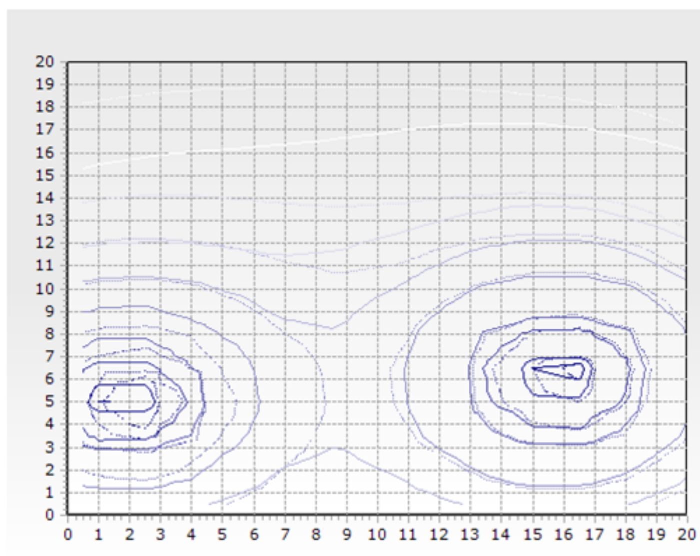


Figure 5: Radiation Map Illustrating Both the Intensity Fields Inferred Using the Developed Method (Solid Lines) and Those Corresponding to Actual Measurements from the "Simulated Environment" in this Study (Dotted Lines).

4 Conclusions

A procedure for generating probabilistic radiation maps using sparse data collected by mobile robots from a small portion of the total area being mapped has been developed. In this method, Bayesian-based techniques are used to infer the most likely location and nature of radiation sources to cause the observed results. Validation of the technique in a simulation study showed that this technique has the potential to be quite effective at characterizing the nature of a radiation intensity field in cases when the radiation model selected is representative of the environment being mapped. The procedure was able to create an accurate map in just over 2,000 MCMC iterations.

5 FUTURE WORK

The integrated approach for creating probabilistic radiation maps using sparse data collected by sensors mounted on mobile robots represents a preliminary validation test. The overarching goal of this research is to create a mobile robotic based tool for generating radiation maps for unknown environments where a geometrical map of the environment does not exist. By combining the procedure presented in this paper with an on-the-fly simultaneous localization and mapping (SLAM) capability and dynamic radiation model development capability, the breadth of potential applications for utilizing probabilistic radiation maps will be increased substantially.

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