MOBILE RADIATION SENSOR NETWORKS FOR SOURCE DETECTION IN A FLUCTUATING BACKGROUND USING GEO-TAGGED COUNT RATE DATA

BY

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THESIS

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Mobile radiation sensor networks integrated with geographic information system provide an attractive option for the real-time anomalous radiation source detection. In order to obtain an accurate alarm of the presence of an anomalous radiation source, continuous measurements of the temporal and positional background radiation distribution are needed. The fluctuations of background radiation can be caused by several reasons, such as the variation in soil composition, building materials, and weather patterns. In this thesis, a radiation sensor network is deployed, and a maximum likelihood estimation-based algorithm is developed to evaluate measurements from the sensor network and estimate the experimental area’s radiation distribution and fluctuation. Using the reconstructed background radiation distribution and fluctuation, the probability that each individual measurement includes an anomalous source is calculated. This thesis presents the work of using statistical inference to adjudicate gamma-ray count-rate data from a sensor network based on measurements of sources in an urban environment. Results show that the maximum likelihood estimation-based algorithm enhances the sensor network’s anomaly detection accuracy over traditional approaches where the background radiation is measured only periodically and considered static in geoposition across large geographic regions.
To my parents, for their love and support.
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CHAPTER 1
INTRODUCTION

1.1 Problem Description

Efficiently monitoring a geographic region’s radiation level and detecting anomalous radiation sources is an important issue in homeland security. In order to continuously monitor a region, measuring the area’s radiation level precisely in both location and time is necessary. Distributed sensor networks offer one potential solution for this task. In previous research, both stationary and mobile detector networks were studied and showed great potential [1, 2]. With measurements from more than one detector, data fusion techniques provided more accurate prediction for anomalous source detection compared with traditional methods such as k-sigma [3]. Bayesian aggregation frameworks are also a promising approach to estimate the likelihood of abnormal source locations in a region [2]. These methods require large amounts of measurements and assume during the experiment that the background radiation level does not change. However, research shows that the background radiation is always fluctuating based on a variety of causes such as weather conditions, (especially precipitation) [4]. This thesis studies the problem of detecting anomalous sources in non-uniformly distributed and fluctuating background radiation environment. A sensor network is deployed on the campus of the University of Illinois, and an algorithm (named the BR-MLE algorithm) based on maximum likelihood estimation method is developed to estimate the background radiation distribution and detect anomalous sources. The main contribution of this thesis is that it provides a way to incorporate the background radiation distribution information into the anomalous source detection.

1.2 Detector Network and Anomaly Detection

With the development of electronics and wireless data communications, wireless sensor networks have attracted more and more research focus in recent years. The basic element of a
A wireless sensor network is a sensor node, which consists of one or more sensors, a processor and memory for data processing, and communication components [5]. The sensor network can be deployed into the environment randomly or with a predefined scheme and gather information from the environment. The sensors used in a wireless sensor network are inexpensive and weaker in functionality compared with traditional sensors. The data processing ability of each node is also limited by the node’s computational resources and energy supply [6]. However, wireless sensor networks can monitor a large region in the environment more efficiently than traditional sensors. Data fusion techniques can also compensate for weak functionality of inexpensive sensors. Wireless sensor networks show potential in target tracking [7], natural environment monitoring [8, 9], and health application [10].

Anomaly detection is also an important application area of wireless sensor networks. In a system, anomalies, outliers, and noise are three important concepts. Anomalies are defined as unexpected behavior of a system. They are not necessarily rare. On the contrary, outliers are defined as rare objects. Noise can be expected, but it is still difficult to predict the system behavior accurately.

Radioactive anomalous source detection is a sub-field of anomaly detection. The count rate fluctuation of background radiation is noise in the overall. For an area at a certain time, this fluctuation can be modeled by a Poisson distribution [11]. Most of the background fluctuations lie in the non-rare event region. The outliers come from both background fluctuations and anomalous sources. Sometimes malicious actions pretend themselves to be normal and make the anomalous source signal lie in the region of normal behavior. This makes anomaly detection task more difficult and requires a more diligent definition about the normal behavior [12].

Another reason making detector networks suitable for anomalous source detection is that a larger detector area may not give a better result [13]. In anomalous source detection, the signal is the radiation from anomalous sources, while the noise is background radiation. An increase in detector efficiency and sensitivity will increase both signal and noise, whereas the strength of the signal, for a given measurement distance, has not changed. Thus, a larger detector cannot provide a higher signal-to-noise ratio in this task. The work of Brennan et al. [14] compared the performance between a distributed detector network and a single detector through simulation. The distributed detector network was composed of 11 NaI detectors. The single detector was a portal monitor with higher detection capability than NaI detectors. Their result showed that even with weaker detectors, the distributed sensor network provided equivalent spectrum and had improved detection capability over portal monitor.
1.3 Algorithms for Source Detection

By comparing and analyzing different measurements from different detectors, detector networks can obtain additional information about anomalous sources and background radiation compared with a single detector. This technique is called data fusion. There are many algorithms traditionally used for radiation detection using detector networks. Generally they can be separated into two groups. One is based on deterministic approach such as the KSigma method and Maximum Likelihood Estimation. The other is based on probability approach such as the Bayesian method. In this section, some popular algorithms will be introduced. These algorithms have one similarity; they require the information about background radiation distribution. The more detailed background radiation the algorithm is fed, the better prediction it can do. This is also the motivation of this thesis.

1.3.1 KSigma

The KSigma method is the most straight forward algorithm among deterministic approaches. For a dataset, the KSigma algorithm first calculates the dataset’s mean value, $\mu$, and standard deviation $\sigma$. For every measurement with gross count $d$, it then calculates the gross count deviation from mean value in the unit of standard deviation as follows:

$$KSigma(d) = \begin{cases} 
\frac{d-\mu}{\sigma}, & \text{if } d > \mu \\
0, & \text{if } d \leq \mu 
\end{cases}$$

(1.1)

If the KSigma value is higher than a predefined threshold, that measurement is predicted to be from an anomalous source. Usually this threshold is chosen as three times $\sigma$. This algorithm is very easy to deploy and can process measurements at high speed. If the dataset is chosen by a rolling time-period window in time series radiation measurements, then this algorithm is able to detect an anomalous source in real time. However, this method assumes that all the measurements are sampled from the same constant background radiation distribution, which is usually not true. If the measurements are taken by a mobile detector, the background radiation should vary spatially depending on the presence of naturally-occurring radioactive materials (NORM) in the environment. Under this case, if the background radiation spatial distribution is known, the prediction from KSigma method can be more accurate.
1.3.2 Maximum Likelihood Estimation

Another famous deterministic approach is the Maximum Likelihood Estimation (MLE) method [15, 16, 17, 18, 19]. In large sample parameter estimation, MLE is popular because it gives the unbiased minimum-mean-square-error estimation when such estimation exists [20]. The minimum estimation error can be calculated based on the Cramer-Rao bound [21], and gives a sense of how good the estimation can be under certain experimental configuration.

The formation of the MLE estimation is a multi-dimension parameter optimization problem. The estimated parameters include source characteristics such as the source’s intensity and location, environment properties such as radiation attenuation coefficients, and background radiation properties such as the distribution and fluctuation of background radiation. The dimension of estimated parameter is related to the number of anomalous sources and number of grid nodes of the experimental area. In order to simplify this problem and get the numerical solution of the MLE problem, most of the MLE methods [15, 16, 17] assume that background radiation is uniformly distributed and constant. By doing this, thousands of parameters to be estimated are removed. Even after this, the grid search method can only solve one source estimation problem [15, 16] due to computation efficiency. Deb [17] proposed a solution based on Fischer’s scoring iterations to solve the MLE. With a good initial estimation about source location and intensity, his solution successfully estimated four sources’ location and intensity. Vilim and Klann [18] took the variation of background radiation into consideration. Their solution was to measure the background radiation at each node for a long time before the experiment. This approach is not always available for mobile detector networks, such as when the detector network is based on public transportation. Bai et al. [19] conducted anomalous source detection under a highly fluctuating background. His method manually assigned different background radiation regions in the map, which requires prior knowledge about a region’s background radiation distribution.

1.3.3 Bayesian Estimation

Bayesian estimation is an important branch in probabilistic methods [22, 23, 24, 3]. This model has a parameter vector $\theta$ that contains all the source and background radiation parameters to estimate, and the dataset $D$ that contains all the measurements. The original knowledge about source and background radiation forms the prior distribution of parameter vector $P_0(\theta)$. The parameter’s posterior distribution $P(\theta)$ is proportional to the product of
prior distribution and the dataset’s conditional likelihood $l(D|\theta)$:

$$P(\theta) \propto l(D|\theta)P_0(\theta)$$ \hspace{1cm} (1.2)

Then those parameters in $\theta$ can be obtained by calculating the expectation of the posterior distribution:

$$\hat{\theta} = E[\theta|D] = \int \theta P(\theta)d\theta$$ \hspace{1cm} (1.3)

These estimated parameters are minimum mean square error estimator of $\theta$ given the measurements $D$. In anomalous source detection problems, the Bayesian estimation problem is solved numerically within a Bayesian filter framework such as particle filters [25], or non-linear Kalman filters [26, 27].

The Bayesian estimation method processes measurements one by one, and continually updates its estimation. Compared with the MLE method, it is faster and more suitable for real-time detection tasks. The result of Bayesian estimation heavily depends on the prior distribution. Under a good prior, a small number of measurements can provide an accurate estimation of source and background radiation. However a bad prior will need a large number of measurements to get a reliable estimation.

### 1.3.4 Bayesian Aggregation

Bayesian aggregation is under the scope of Bayesian estimation, but with a different math structure. Instead of estimating parameters of the anomalous source and background radiation, it estimates the probability of a place to have anomalous sources [2]. If a high gross count is measured, the areas around this measurement will have a higher probability to have anomalous sources. With those probabilities, a probability map of detection area is drawn indicating the probability of each place to have anomalous sources. Given a measurement, the Bayesian aggregation algorithm first evaluates the measurement’s probability of coming from an anomalous source based on spectrum information. With that probability, the algorithm then updates the probability map using Bayesian rule. This algorithm is scalable and can be deployed in real time. In order to evaluate each measurement’s probability of belonging to anomalous sources, either a good spectrum or a good knowledge about the background radiation distribution is required. In a real application, the time interval for each measurement is limited and the spectra are usually of poor quality. Thus a detailed background radiation distribution is important.
1.3.5 Other Algorithms

There are other deterministic algorithms such as inverse-law inference [28, 29, 30], and probabilistic algorithms such as weighted least squares estimation methods [31]. It was also shown that the solution from weighted least squares estimation is equivalent to the solution of the MLE method [17].

1.4 Related Works

As discussed in Section 1.3, it is important to track background radiation and recognize the background radiation component in each measurement. For a measurement with adequate detection time, it is necessary to be able to recognize and separate background radiation and anomalous source radiation based on the shape and peaks in the spectrum. However, the detection time is usually limited and can be as short as one second in anomalous source detection. With such a short interval, a regular hand-held mobile detector based on inorganic scintillators can only gather dozens of events. The background radiation and anomalous source radiation can not be easily separated based on the spectrum under this situation. For the background radiation tracking problem, different solutions are introduced such as spectral comparison ratios, filter-based methods and machine learning-based methods.

The spectral comparison ratio (SRC) technique was developed by Pfund et al. to compare unknown spectra with pre-defined nuisance source spectra [32, 33, 34]. Their work demonstrated that this approach could be tuned to be sensitive to special radiation materials, was able to work under low count rate situations and improved detection ability over the gross-count approach. Besides SRC, match filters [2] and energy windowing regression [35] are other approaches to use source templates to match and extract source features in unknown spectrum.

Kalman Filters were used to track and predict background radiation fluctuation [36, 37]. It was observed that elevated background radiation from one measurement was likely to stay elevated in the next observation, which indicated that background estimation could be improved by tracking background fluctuation over time [36]. Jarman et al.’s simulation results showed that the Kalman Filter method reduced the variation in residual count levels and made improvement in anomalous source detection.

Principle component analysis (PCA) was also studied to recognize source and background components in unknown spectrum [38, 2]. This method needs training data to train the algorithm recognizing the so-called principle components in the spectrum. These principle components are the bases of the spectrum and contain most of the variation of the dataset.
When a new measurement is obtained, it will be projected to the principle components to separate the background and source components.

Kernel-based machine learning method were also applied to estimate background radiation in low-count rate environment [39]. A Gaussian process was used to reconstruct the background spectrum, and different kernels were compared.

1.5 Chapter Overview

This thesis has 5 chapters in total. The first chapter introduces the problem of anomalous source detection, and gives an overview of the sensor network and anomaly detection. The second chapter describes the mathematical model for anomalous source detection, and proposes an initial algorithm for background radiation estimation using a maximum likelihood estimation BR-MLE approach. The third chapter describes the setup of the experiments that tested the performance of the BR-MLE algorithm in anomalous source detection. The fourth chapter discusses the results of those experiments, and shows that the BR-MLE algorithm reduced the false positive rate compared to the KSigma method. The fifth chapter summarizes this thesis, and lists the possible future work.
CHAPTER 2

METHODS

2.1 Background Radiation Maximum Likelihood Estimation Algorithm

A background radiation maximum likelihood estimation (BR-MLE) algorithm is developed to extract the background radiation information from a large number of measurements taken at different times and in different locations. This algorithm is able to estimate the background radiation’s spatial distribution and time variation. Only the gross count information of each spectrum is used in this thesis.

2.1.1 Assumptions for BR-MLE algorithm

Based on the anomaly-source detection task, several assumptions are made for the distribution and variation of background radiation.

The first assumption suggests that for an area that is small enough, the background radiation distribution in that area should be uniformly distributed. It is based on the fact that the majority of background radiation is come from radioactive isotopes in air, soil, and building materials. In fields or cities, these background radioactive sources are always uniformly distributed in regions small enough. In this thesis, these regions are chosen as small as $4m \times 6m$.

The second assumption is that the fluctuation behavior of background radiation is the same across an area if this area is uniformly impacted by the cause of the background radiation fluctuation. For example, precipitation is a known cause for the increase of background radiation [4]. At a given time, the weather doesn’t change a lot for a region as small as a block on campus, which is chosen as our experimental region with an area around $10^5 m^2$. The background radiation fluctuation caused by precipitation is assumed to be the same across the entire experimental region.

The third assumption is that the anomaly radioactive source can be treated as a point
source in the environment. Shielded nuclear weapons, and radioactive sources for industry or medical application are examples of anomaly sources. These sources can be treated as point sources in the scale of a city or a block in the city. With assumption one and assumption three, an anomalous radioactive source can be recognized because the existence of the anomaly source will break background radiation’s uniform distribution.

2.1.2 Modeling of background radiation estimation

With the three assumptions above, the background radiation estimation task is modeled with a Poisson distribution.

For a given measurement taken at time \( t \) and position \((x, y)\), the gross count \( d(x, y, t) \) of that measurement corresponds to a unique Poisson parameter \( \lambda(x, y, t) \). This \( \lambda \) is a function of position and time. According to assumption one and assumption two, the \( \lambda(x, y, t) \) is separable between position \((x, y)\) and time \( t \). Thus the \( \lambda \) can be rewritten as follows:

\[
\lambda(x, y, t) = \lambda_1(x, y) + \lambda_2(t) \tag{2.1}
\]

\( \lambda_1(x, y) \) is a Poisson parameter representing the background radiation’s spatial distribution corresponding to building materials and soil components. These radioactive sources do not change with time, but have different distributions at different positions. Gross counts from these radioactive sources can be modeled with Poisson distributions with spatially distributed Poisson parameters \( \lambda_1(x, y) \). \( \lambda_2(t) \) is another Poisson parameter standing for background radiation’s temporal fluctuation (i.e. caused by weather conditions). According to assumption two, such fluctuation is a function of time, and is independent of position in experimental area.

There are many ways to construct \( \lambda(x, y, t) \) from \( \lambda_1(x, y) \) and \( \lambda_2(t) \). The reason to choose Equation 2.1 is as follows: \( \lambda_1(x, y) \) and \( \lambda_2(t) \) are independent Poisson parameters standing for different background radiation sources with different distribution/fluctuation patterns; the summation of a Poisson distribution is also a Poisson distribution.

With Equation 2.1, the probability \( P[d(x, y, t)] \) that measurement \( d(x, y, t) \) comes from the background radiation distribution \( \lambda_1(x, y) \) and \( \lambda_2(t) \) can be calculated as follows:

\[
P[d(x, y, t)] = \frac{\lambda^{d(x, y, t)} e^{-\lambda}}{d(x, y, t)!} \tag{2.2}
\]

where \( \lambda = \lambda_1(x, y) + \lambda_2(t) \)

The data set \( D \) is defined to contain every measurement \( d(x, y, t) \) of the experiment. \( X, Y \)
and \( \mathcal{T} \) are defined to be the collections of measurements longitude, latitude and time. The probability \( P[\mathcal{D}] \) that all the measurements come from background radiation distribution \( \lambda_1(x, y) \) and \( \lambda_2(t) \) is derived as follows:

\[
P[\mathcal{D}] = \prod_{d(x,y,t) \in \mathcal{D}} P[d(x,y,t)] \\
= \prod_{x \in X} \prod_{y \in Y} \prod_{t \in \mathcal{T}} P[d(x,y,t)] \\
= \prod_{x \in X} \prod_{y \in Y} \prod_{t \in \mathcal{T}} \frac{\lambda_{d(x,y,t)} e^{-\lambda} d(x,y,t)!}{d(x,y,t)!} \\
\text{where } \lambda = \lambda_1(x, y) + \lambda_2(t) \tag{2.3}
\]

The natural logarithm on both sides of the Equation 2.3 can be calculated to obtain the log-likelihood of dataset \( \mathcal{D} \):

\[
l[\mathcal{D}] = \log(P[\mathcal{D}]) \\
= \log(\prod_{x \in X} \prod_{y \in Y} \prod_{t \in \mathcal{T}} \frac{\lambda_{d(x,y,t)} e^{-\lambda} d(x,y,t)!}{d(x,y,t)!}) \\
= \sum_{x \in X} \sum_{y \in Y} \sum_{t \in \mathcal{T}} \log(\frac{\lambda_{d(x,y,t)} e^{-\lambda} d(x,y,t)!}{d(x,y,t)!}) \tag{2.4}
\]

Bringing Equation 2.1 into Equation 2.5 the final expression of log-likelihood is obtained:

\[
l[\mathcal{D}] = \sum_{x \in X} \sum_{y \in Y} \sum_{t \in \mathcal{T}} \log(\frac{(\lambda_1(x, y) + \lambda_2(t)) d(x,y,t) e^{-(\lambda_1(x,y) + \lambda_2(t))} d(x,y,t)!}{d(x,y,t)!}) \\
= \sum_{x \in X} \sum_{y \in Y} \sum_{t \in \mathcal{T}} \left\{ d(x,y,t) \log(\lambda_1(x,y) + \lambda_2(t)) \right. \\
- \lambda_1(x,y) - \lambda_2(t) - \log(d(x,y,t)!) \left. \right\} \tag{2.5}
\]

### 2.1.3 Discrete Model

Once the log-likelihood function \( l[\mathcal{D}] \) is obtained, the best estimation for background radiation distribution and fluctuation can be calculated by maximizing the log-likelihood function. However, all the measurements are discrete in time and position, and the three assumptions imply that the experimental region is separated into a mesh. This problem is a discrete
problem and the probabilistic model should be converted into a discretized form for further analysis.

According to assumption one, the experimental region is divided into small subareas. In each of these subareas, the background radiation’s spatial Poisson parameter $\lambda_1(x, y)$ is the same. As shown in Figure 2.1, the discrete model uses $i$ and $j$ to count each subarea in the direction of longitude and latitude. The experimental data set is also separated into different time periods $k \in \{1, 2, 3, \ldots\}$. In each of these time periods, the background radiation’s temporal Poisson parameter $\lambda_2(t)$ is the same. With this modification, the Poisson parameters can be represented as the following:

$$
\lambda_1(x, y) = \lambda_{ij}^1, \text{ where } (x, y) \text{ is in subregion } (i, j) \\
\lambda_2(t) = \lambda_k^2, \text{ where } t \text{ is in time period } k.
$$

Because the last term in Equation 2.5 is a constant and has nothing to do with Poisson parameters, it will be ignored in the following derivation. The log-likelihood function can be revised as the following:

$$
\begin{align*}
\log \mathcal{L}[D] & = \sum_{x \in X} \sum_{y \in Y} \sum_{t \in T} \left\{ d(x, y, t) \log(\lambda_1(x, y) + \lambda_2(t)) - \lambda_1(x, y) - \lambda_2(t) \right\} \\
& = \sum_{i, j, k} \left\{ d_{ijk} \log(\lambda_{ij}^1 + \lambda_k^2) - n_{ijk}(\lambda_{ij}^1 + \lambda_k^2) \right\}
\end{align*}
$$

$d_{ijk}$ is the summation of all measurements’ gross counts in subregion $(i, j)$ within time period $k$. $n_{ijk}$ is the number of measurements taken in subregion $(i, j)$ within time period $k$:

$$
\begin{align*}
d_{ijk} & = \sum_{x \in i} \sum_{y \in j} \sum_{t \in k} d(x, y, t) \\
n_{ijk} & = \sum_{x \in i} \sum_{y \in j} \sum_{t \in k} \frac{d(x, y, t)}{d(x, y, t)}
\end{align*}
$$
2.1.4 Maximum Likelihood Function

2.1.4.1 Optimization Algorithm Discussion

With the previous preparation, the optimized background radiation estimation can be calculated from Equation 2.7:

\[
\lambda_{ij}^1, \lambda_{ij}^2 = \arg \max_{\lambda_{ij}^1, \lambda_{ij}^2} \sum_{i,j,k} \left\{ d^{ijk} \log(\lambda_{ij}^1 + \lambda_{ij}^2) - n^{ijk}(\lambda_{ij}^1 + \lambda_{ij}^2) \right\}
\] (2.9)

This optimization task is a high dimension problem with a large number of parameters to optimize. For this demonstration, the experimental area is approximately \(10^5 m^2\). Given a subdivision of the discrete to be approximately \(25m^2\), the number of elements in \(\lambda_1\) is on the order of \(10^3\) to \(10^4\). Also, if the experiment lasts for one month and the time period is defined as every 24 hours, \(\lambda_2\) will have 30 elements. In total, the number of parameters to be optimized in this problem is on the order of \(10^3\) to \(10^4\).

The most straightforward way to find the optimized solution is to calculate the value of the log-likelihood function for all possible parameter values. However, trying out all combinations of values of all parameters is impossible for this problem. In this thesis, a specially-designed grid search method was developed to find the global optimal solution.
This method is called the brute force algorithm.

2.1.4.2 Brute Force Algorithm

The derivatives of $\lambda_1^{ij}$ and $\lambda_2^k$ are calculated as following:

$$d\lambda_1^{ij} = \frac{\partial l[D]}{\partial \lambda_1^{ij}} = \sum_k \left( \frac{d^{ijk}}{\lambda_1^{ij} + \lambda_2^k} - n^{ijk} \right)$$

$$d\lambda_2^k = \frac{\partial l[D]}{\partial \lambda_2^k} = \sum_{ij} \left( \frac{d^{ijk}}{\lambda_1^{ij} + \lambda_2^k} - n^{ijk} \right)$$

(2.10)

At the maximum point of the log-likelihood function, the derivatives of $\lambda_1^{ij}$ and $\lambda_2^k$ should be zero. Thus the task of finding $\lambda_1$ and $\lambda_2$ that maximize the log-likelihood function is converted to finding $\lambda_1$ and $\lambda_2$ that make their derivatives close to zero. This task can be written as follows:

$$\lambda_1^{ij} = \arg \min_{\lambda_1^{ij}} \left| \sum_k \left( \frac{d^{ijk}}{\lambda_1^{ij} + \lambda_2^k} - n^{ijk} \right) \right|$$

$$\lambda_2^k = \arg \min_{\lambda_2^k} \left| \sum_{ij} \left( \frac{d^{ijk}}{\lambda_1^{ij} + \lambda_2^k} - n^{ijk} \right) \right|$$

(2.11)

Equation 2.11 shows that parameters of Equation 2.7, such as $\lambda_1$ and $\lambda_2$, are not independent of each other. Thus the potential parameter space for the log-likelihood Equation 2.7 is much smaller than all combinations of parameters. Though it is impossible to do grid search in all combinations of parameters, it is possible to do it in this smaller parameter space. It is also noticed from Equation 2.11 that all the elements of $\lambda_1$ are independent with each other when $\lambda_2$ is given, and all the elements of $\lambda_2$ are independent with each other when $\lambda_1$ is given. Based on these properties, the rule to update $\lambda_1$ and $\lambda_2$ is designed. An arbitrary set of $\lambda_1$ and $\lambda_2$ is given. Then $\lambda_1$ is updated based on $\lambda_2$, and $\lambda_2$ is updated based on the new updated $\lambda_1$. This process will be terminated when the value of log-likelihood function meets some predefined criteria. Though in math the derivatives of $\lambda_1$ and $\lambda_2$ equaling to zero doesn’t ensure that the log-likelihood function has reached its maximum value, in a real application this method converges on the correct solution. The result of the brute force algorithm will be discussed in Chapter four. The pseudocode is as follows:
**Algorithm 1 Brute Force Algorithm**

Initialize $\lambda_1, \lambda_2, l(\lambda_1, \lambda_2)$

while $l(\lambda_1, \lambda_2)$ doesn’t converge do

$\lambda_{ij}^1 = \arg \min_{\lambda_{ij}^1} \left| \sum_k (d_{ijk} - n_{ijk}) \right|$ for all $i,j$

$\lambda_k^2 = \arg \min_{\lambda_k^2} \left| \sum_{ij} (\frac{d_{ijk}}{\lambda_{ij}^1 + \lambda_k^2} - n_{ijk}) \right|$ for all $k$

$l(\lambda_1, \lambda_2) = \sum_{i,j,k} \left\{ d_{ijk} \log(\lambda_{ij}^1 + \lambda_k^2) - n_{ijk}(\lambda_{ij}^1 + \lambda_k^2) \right\}$

end while

2.2 Alarm Trigger Algorithm

With the estimated background distribution $\lambda_{ij}^1$ and $\lambda_k^2$, every measurement’s corresponding background radiation Poisson parameter can be estimated. For measurement $d(x, y, t)$ taken in grid $(i, j)$ at time period $k$, the Poisson parameter estimation $\lambda(d)$ is:

$$\lambda(d(x, y, t)) = \lambda_{ij}^1 + \lambda_k^2$$ (2.12)

The probability to observe event $d(x, y, t)$ from Poisson distribution with parameter $\lambda(d)$ is

$$P(d(x, y, t)) = \frac{e^{-\lambda} \lambda^{d(x,y,t)}}{d(x,y,t)!}$$ (2.13)

where $\lambda = \lambda(d(x, y, t)) = \lambda_{ij}^1 + \lambda_k^2$

This probability can be interpreted as the probability that measurement $d(x, y, t)$ purely comes from background radiation. If this probability is very small, it means measurement $d(x, y, t)$ potentially includes an anomalous source. An alarm will be triggered and this measurement will be flagged for further tests and analysis.
3.1 Experiment Platform

There were two major components in the hardware setup: the detector network, and the anomalous sources. The detector network was composed of Kromek D3s detectors and Samsung Galaxy S6 Android phones. The anomalous sources in the experiments were Ra-226 brick sources with an activity of approximately 10 µCi.

3.1.1 Detector Network

The detector network was composed of detection nodes. As shown in Figure 3.1, each node had a Kromek D3s detector, and an Android phone. Every node recorded the gamma-ray count rate and spectrum, the thermal neutron count rate, and the geocoordinates in a time interval of one second. Each of these nodes acted as an individual mobile detector. The data of each node was uploaded through a cellular network into a database for further analysis. The Android phone was connected to the D3s detector through Bluetooth connection. For every second, the phone received a spectrum taken by the D3s detector, and queried the geographic information from GPS module in the phone. Then the phone uploaded the spectrum together with geocoordinates into a database through a cellular network. The phones worked as intermediate processors that collected the data from detectors and sent the data to a database. It could also run light-weighted algorithms such as kSigma to detect for obvious anomalous sources.

The D3s detector had a CsI(Tl)/silicon photo-multiplier-based gamma-ray detector, and a thermal neutron scintillator detector. The CsI(Tl) scintillator’s size was 2”x1”x0.5”. Its gamma-ray energy range was 30keV to 3MeV, and its maximum count rate was 10,000cps. Figure 3.2 shows the Cs-137’s spectrum taken by a D3s with a sufficiently long detection time that was 337 seconds. Its energy resolution was 7% at 662keV. As a comparison, Figure 3.3 shows the spectrum of background and Cs-137 taken by a D3s with a time interval of
one second, which is representative of the true operating conditions of this type of sensor network. Both of the background spectrum and the Cs-137 spectrum are of low quality, and the 662keV peak is difficult to recognize. In this thesis, only the gross count information of each spectrum was used.

The sensor network had 23 nodes running on campus continuously collecting data. These detectors were carried by students from the University of Illinois, and they recorded radiation information from everywhere they went.

3.1.2 Anomalous Source

The anomalous sources used in this work were Ra-226 bricks with an activity of approximately 10 $\mu$Ci each. As shown in Figure 3.4, the bricks were put into a cart and deployed in the experimental area. Figure 3.5 shows the gross counts from Ra-226 brick sources at
Figure 3.2: Gamma-ray spectrum of Cs-137 taken by D3s detector. The integration time was 337s and energy resolution was 6.97% at 662 keV.

different detection distances. These gross counts were taken under an average background radiation of 18.75 cps, and the background radiation’s standard deviation was $\sigma = 4.48$ cps. When the detection distance was smaller than 1.8m, the gross count from source exceeded the $3\sigma$ range of background radiation. Beyond this range, it was difficult to use $3\sigma$ method to judge whether this gross count was from background radiation, or from anomalous sources due to the low signal-to-noise ratio.

3.2 Experiment Design

In order to test the background radiation estimation algorithm’s performance in the anomalous source detection, three experiments were conducted. The first experiment tested the detector network GPS signal’s accuracy. The second experiment tested the algorithm’s performance in the estimation of background radiation. The third experiment tested the algorithm’s ability to detect anomalous sources.
3.2.1 GPS Signal Correction

An accurate estimation of the background radiation distribution and anomalous source position is based on an accurate GPS signal. However, the GPS signal was easily affected by various factors. Cloudy weather reduced the accuracy of the GPS signal, and buildings blocked the GPS signal and caused the device to lose location service temporary. Moreover, the update frequency of the GPS signal was much lower than the radiation measurements being collected by the detector. In order to obtain the correct location of each measurement, an interpolation method was applied to calculate a measurement’s location from the GPS data.

In this experiment, two operators walked in predefined paths as shown in Figure 3.6. Each of the operators carried two nodes of the detector network. This experiment collected raw GPS signal, evaluated the GPS signal’s accuracy and tested the linear interpolation algorithm for the GPS signal.
3.2.2 Background Radiation Estimation

This experiment tested the BR-MLE algorithm’s performance to estimate background radiation. Eleven days’ data from one node was selected to estimate the campus background radiation distribution.

The carrier of this node was not informed about this experiment, and the movement of this node was not restricted or predefined. Figure 3.7 shows the active area and experimental area of this node. Over the course of eleven days, the active area of this node covered a large region of Urbana, IL and Champaign, IL. The measurements from this experiment were taken under different radiation-shielding situations, such as walking and taking a bus. For the same path, the gross counts measured when the node carrier was walking were much higher than those measured when the node carrier was taking a bus. The variations were caused by the body of the bus shielding some of the background radiation. In order to obtain measurements with the same radiation shielding configuration, an experimental area
was selected as shown in Figure 3.7. This experimental area was located on the campus of University of Illinois, and most of the measurements within this area were taken while the node carriers were walking. The data analysis of background radiation estimation was based on the measurements within this experimental area.

3.2.3 Anomalous Source Detection

In the anomalous source detection experiment, a sensor network with 3 nodes was deployed in an experimental area to locate eight anomalous sources. The BR-MLE algorithm was used to estimate the experimental area’s radiation distribution, and find the anomalous sources. The result of the BR-MLE algorithm was then compared with the result of the kSigma algorithm.

As shown in Figure 3.8, the experiment area was 450 meters long and 300 meters wide. This area had naturally high background radiation spots. The areas in the orange box...
in figure 3.8 were generally three to five sigma above background because of the building materials. The anomalous source in this experiment was a Ra-226 brick with an activity of approximately $1\mu Ci$. The experiment consisted of six days’ worth of measurements from Dec. 10, 2015 to Dec. 15, 2015. On each day of Dec 11th and 15th, the anomalous source was placed in one of four different locations within 3 meters of the path in the experiment area. Three experiment operators walked in predefined paths with one mobile detector per person. As shown in Figure 3.8, these paths were confined to sidewalks and streets. Their geopositions and radiation count rates were automatically recorded once per second. On Dec 10th, 12th, 13th and 14th, no sources were placed in the experiment area and only a limited scan was conducted. In the limited scan, only one experiment operator carrying one detector participated in the experiment and covered only part of the experiment area. The limited scan was used to gather the background fluctuation data.
Figure 3.7: The experimental region for the background radiation estimation experiment.

Figure 3.8: The experimental region for the anomalous source detection experiment.
CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 GPS Signal Correction

In this experiment, the accuracy of GPS signal was evaluated, and a GPS signal correction method was developed based on the linear time interpolation method. This method could correct the inaccurate GPS locations that resulted from the low GPS signal updating rate. The final GPS signal accuracy after correction was limited by the intrinsic GPS signal accuracy, which was approximately 10 meters.

4.1.1 Interpolation of GPS Signal

Figure 4.1 shows a single node’s track in GPS signal correction experiment could be seen. During the experiment, this node ran four loops of this track. The track before interpolation was discrete and sparse, while the track after interpolation was smooth. This was due to the GPS signal’s updating frequency being lower than the spectrum’s updating frequency. If a new spectrum arrived but the GPS signal was not updated due to the low updating rate, this new spectrum will use a previous measurement’s GPS data. Many measurements shared the same GPS location and were shown in the map at the same point. Thus, the GPS track before interpolation was discrete and sparse. Through the interpolation, every measurement’s location was re-calculated based on the successful GPS queries, and was closer to the true position where the measurement was taken.

The interpolation algorithm was based on the linear-time interpolation method. It assumed that within a short time interval, such as 10 seconds, the node’s track should be a straight line. This assumption held because generally people walked in a straight line to achieve the shortest path, and the experiment operators were told to keep their walking path straight. The tracks were also more distinct from each other after interpolation, as shown in the second row of Figure 4.1.
4.1.2 Consistency of GPS Signal

This experiment also tested the consistency of GPS signal between different nodes. During the experiment, each operator carried two nodes at the same time. Ideally, the tracks from these two nodes should be the same. Figure 4.2 showed the tracks of two nodes carried by the same operator. Though the overall shape of two tracks were similar, the deviations of the two tracks were as large as 10 meters.

This experiment showed that the linear-time interpolation method could correct the inaccurate locations of measurements due to a low GPS signal updating rate. However, the final location accuracy after interpolation is still limited by the GPS signal accuracy.

4.2 Background Radiation Estimation

In this experiment, the BR-MLE algorithm used 11 days’ measurements from a single node to estimate the experimental area’s background radiation distribution. A data cleaning method was developed to select measurements with the same radiation shielding conditions.
The BR-MLE algorithm was then shown to be convergent with different initial conditions. Lastly, the estimated background radiation distribution from BR-MLE was shown to be a better way to estimate each measurement’s gross count compared with the mean value of the total dataset.

4.2.1 Data Cleaning

Figure 4.3 showed the node’s path during the experiment. This path recorded the node carrier’s footprint during the 11 days. The path clearly showed that the node carrier took buses during the 11 days, for some of the path followed the roads and streets of Champaign and Urbana. The path also recorded the node carrier’s walking routes on campus, and many of these routes overlap one another. Figure 4.4 showed the density distribution of measurements with different gross count and speed. The joint density distribution in Figure 4.4 showed that the measured gross count rate was strongly associated with the node’s speed. There were two clusters that appeared in Figure 4.4 (A). The first cluster had a higher speed, but a lower gross count. The second cluster had a lower speed, but a higher gross count. The first cluster was formed by measurements recorded when the node carrier was taking a
bus, while the second cluster was formed by measurements recorded when the node carrier was walking. When the carrier was on a bus, the speed of the node was higher and the background radiation was partly shielded by the bus. When the carrier was walking, the node was nearer to naturally occurring radiation sources in the environment such as the ground and higher gross counts were recorded. Figure 4.4 shows the influence of different transportation methods on the radiation shielding situation, and on the gross counts. The BR-MLE method required that the radiation shielding situation should stay the same for all the measurements. Measurements with the same radiation shielding situation should be selected from the 11 days’ dataset.

Figure 4.3: The location distribution of 11 day’s measurements.

There were three major radiation shielding situations during the experiment: walking, taking a bus, and staying in buildings. In order to analyze the campus’ background radiation distribution, the measurements recorded when the node carrier was walking on campus should be kept and the rest should be filtered out. The speed of the node was an indicator for these three radiation shielding situations. When the node carrier stayed in buildings, the
node’s speed was zero. When the node carrier was walking on campus, the node’s speed was between 0 and 2m/s. When the node carrier was on a bus, the node’s speed was usually greater than 2m/s. The ‘walking’ measurements could be separated out by selecting the measurements with speed between 0 to 2m/s. However, there were numerous crossings and stop signs on campus and the bus stopped frequently. Many measurements taken on buses had speeds lower than 2m/s. In order to filter these measurements out, a speed-smooth method was developed to calculate the node’s average speed within a time window. Figure 4.5 shows a series of measured speeds before and after smoothing. From time 0 to 60 seconds,
the node’s carrier was on a bus. This bus stopped twice at 30 seconds and 60 seconds. The node carrier got off the bus and started to walk at 60 seconds. Without speed smoothing, the 2 m/s speed threshold would wrongly identified the measurements between 20 and 35 second as walking. The corresponding radiation measurements in that time period were actually taken on a bus and had a significantly lower gross count. These measurements would influence the estimation of the BR-MLE algorithm. After speed smoothing, the 2 m/s speed threshold could clearly separate the difference between walking and taking a bus.

![Figure 4.5: The speed of a series of measurements before and after speed-smoothing.](image)

Finally, this experiment had two steps in data cleaning. Firstly, an experimental area was selected as shown in Figure 4.3. This area was the core area of the campus and 84% of the measurements within this area were taken while walking. Measurements outside of this area were abandoned. Secondly, the measurements within the experimental area were filtered by the smoothed speed. Only the measurements with smoothed speeds between 0 to 2 m/s were kept, otherwise they were abandoned.
4.2.2 Convergence of the BR-MLE algorithm

As discussed in Section 2.1.4, the BR-MLE algorithm required an initial $\lambda_1$ and $\lambda_2$ to start the calculation. For a given dataset, BR-MLE found the global optimal solution for the MLE problem. With this global optimal solution, the log likelihood of Equation 2.7 should achieve its maximum value. The global optimal solution should be independent of the initial conditions, and the maximum value of the log likelihood function should converge to the same value under different initial conditions. In this section, ten different initial conditions were used to test the convergence of the BR-MLE algorithm. For the first five initial conditions, each element of $\lambda_1$ was randomly selected between 0 and 100 and each element of $\lambda_2$ was randomly selected between -10 and 10. For the second five initial conditions, all the elements of $\lambda_1$ had the same value that was randomly selected between 0 and 100 while all the elements of $\lambda_2$ had the same value that was randomly selected between -10 and 10. Figure 4.6 shows the values of log likelihood function at different iterations under different initial conditions. After 15 iterations, all of the log likelihood functions under different initial conditions converged to the same value. This convergence meant that the BR-MLE algorithm found the correct global optimal solution for the MLE problem.

4.2.3 Estimated Background Radiation Distribution

The estimated background radiation distribution from BR-MLE algorithm is shown in Figure 4.7. Colored regions illustrate the areas covered by the node during the 11 day’s experiment. As is evident in the figure, the background radiation was not uniformly distributed in the experimental area. Two high background radiation areas were identified as the red spots around the Nuclear Radiation Laboratory in Figure 4.7. The highest background radiation area was around the Nuclear Radiation Laboratory with an averaged gross count of 77 cps. Figure 4.8 shows the statistical properties of estimated background radiation levels. The median and mean background radiation levels in the experimental area were both 30 cps. 50% of the area’s background radiation was between 26 and 34 cps. The box plot also had 6 outliers. These outliers’ background radiation levels were all above 46 cps, which was 3 standard deviations above the mean value of background radiation. The KSigma method usually used 3 standard deviations above the mean value as the alarm threshold. For traditional source detection methods such as the KSimga method, background radiation measurements taken from those outlier measurements would be recognized as sources.

The estimated background radiation distribution $\lambda_1$ and $\lambda_2$ could be used as a estimator
Figure 4.6: Convergence of BR-MLE algorithm with different initial conditions. The figure on bottom is a zoomed-in version of the figure on top.

\[ \hat{d}_{MLE}(x, y, t) \] of the measurement \( d(x, y, t) \):

\[ \hat{d}_{MLE}(x, y, t) = \lambda_1^{ij} + \lambda_2^k \]  \hspace{1cm} (4.1)
Figure 4.7: Estimated background radiation distribution in the experimental area.
where \((x, y)\) was in subregion \((i, j)\), and \(t\) was in time period \(k\). Without considering the background radiation fluctuation, the estimator for measurement \(d(x, y, t)\) was the mean value of the whole dataset \(D\):

\[
\hat{d}_\mu(x, y, t) = \text{Mean}[D]
\]  

(4.2)

Figure 4.9 compared the estimation error between \(\hat{d}_\mu\) and \(\hat{d}_{\text{MLE}}\). By using background radiation distribution information, the \(\hat{d}_{\text{MLE}}\) had a better overall estimation performance compared with \(\hat{d}_\mu\) based on the fact that estimation error’s range was reduced from \((-30, 35)\)
cps to $(-20, 20)$ cps and estimation error’s standard deviation was reduced from 14.6 cps to 10.7 cps.

![Box plot of estimation error using mean value $\hat{d}_\mu$ and BR-MLE $\hat{d}_{MLE}$.](image)

Figure 4.9: The box plot of estimation error using mean value $\hat{d}_\mu$ and BR-MLE $\hat{d}_{MLE}$.

### 4.3 Anomalous Source Detection

In this experiment, a three-node detector network was deployed to locate 8 anomalous sources in an experimental area with high background radiation regions illustrated by Figure 3.8. Both the BR-MLE algorithm and the KSigma algorithm were used to predict the location of the 8 anomalous sources. Results show that both BR-MLE and KSigma successfully found all of the eight anomalous sources, while the BR-MLE’s false alarm rate was lower than the KSigma.
4.3.1 Estimation of Background Radiation Distribution

The BR-MLE firstly calculated the background radiation distribution of the experimental area using all of the measurements. Figure 4.10 illustrated the estimated background radiation distribution. The uncolored area of the map in Figure 4.10 was not covered by this experiment, and thus had no background radiation estimations. Areas around the previously-identified regions of higher background in Figure 3.8 had higher radiation count rates, as expected. The church area was 5.3-sigma above background. Nuclear Radiation Laboratory (NRL) area and Alma Mater area were 3.7-sigma above background. As shown in Figure 4.11, traditional methods such as KSigma will wrongly recognize the high background areas as sources, since the radiation level in these areas were already comparable with anomalous sources.

![Figure 4.10: The estimated background radiation distribution of the experimental area.](image)

4.3.2 Anomalous Source Detection

In this section, the BR-MLE algorithm and the KSigma algorithm were used to identify the measurements which exceeded the alarm threshold. The BR-MLE algorithm used the information from background radiation distributions to find measurements that detected anomalous sources. In contrast, the KSigma method only used the mean value and the
standard deviation of the whole dataset to identify which measurements detected the source. For both of these two algorithms, the relevant parameters were carefully tuned according to each day’s measurements. Each of the two algorithms had different alarm thresholds for different days such that these thresholds obtained the lowest false alarm rate, while finding all of the sources presented during that day’s experiment.

Figure 4.11 compared the performance of the BR-MLE algorithm and the KSigma algorithm in the detection of the anomalous sources. The BR-MLE algorithm detected all of the eight sources to an accuracy of 30 meters without any false positive event. The KSigma algorithm detected all of the eight sources. However, it also generated false positive events which were concentrated in the high background areas. The dispersion of detected sources around the true source location was a result of the deviations of the GPS signal.

![Figure 4.11: Estimated source position from BR-MLE algorithm and KSigma algorithm.](image)

4.3.3 ROC Curve of BR-MLE and KSigma Algorithm

The performances of the BR-MLE algorithm were also compared with the KSigma algorithm via the receiver operating characteristic (ROC) curve. The ROC curve is a standard metric for a binary classifier system, and plots the classifier’s true positive rate v.s. false positive rate. For this problem, the binary classifier decided whether the measurement detected the anomalous source or not. For a given alarm threshold, the false positive rate and true
positive rate of that classifier can be calculated. The ROC curve was then drawn by varying the alarm threshold.

Figure 4.12 compares the ROC curves of the BR-MLE algorithm and the KSigma algorithm. The area under the ROC curve (AUC) formed a metric for the performance of the two different algorithms. The larger the AUC, the better overall performance the classifier has. Table 4.1 compares the BR-MLE algorithm and the KSigma algorithm’s true positive rates at different false positive rates, and compares the two algorithms’ AUC values. The BR-MLE’s AUC value was larger than the KSigma’s which meant that the BR-MLE algorithm had a better overall performance than the KSigma method. The ROC curve also showed that the major improvement of the BR-MLE algorithm over the KSigma algorithm was in the low false positive rate region. It was because the BR-MLE used the background radiation information to make predictions. Its decision was not likely to be affected by the fluctuation of background radiation. On the contrary, the KSigma method only used the first and second order expectations of the whole dataset to make predictions. This made the KSigma method vulnerable to fluctuating background radiation.

![Figure 4.12: The ROC curve of the BR-MLE algorithm and the KSigma algorithm.](image)

This experiment showed that after using the information from background radiation distributions, the BR-MLE provided accurate anomalous source detections with low false alarm rates. Compared with the KSigma method, the BR-MLE algorithm had improved detection
ability in the low false positive range.

Table 4.1: Comparison of true positive rate (TPR) and area under the curve (AUC) between the BR-MLE method and the KSigma method.

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<th>TPR</th>
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<tr>
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CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

This thesis studied the anomalous source detection under a fluctuating radiation background. A mobile radiation sensor network consisting 23 nodes was deployed on the campus of the University of Illinois to measure the background radiation distribution and to detect anomalous sources. A maximum likelihood estimation based algorithm, which was called the BR-MLE algorithm, was developed for estimating the spatial distribution and temporal fluctuation of the background radiation. A detection scheme was proposed to identify anomalous sources using the background radiation distribution calculated by the BR-MLE algorithm. This approach reduced the false positive rate compared to the KSigma method during the test of this thesis.

This thesis explored potential difficulties in detecting for anomalous sources with mobile sensor networks and possible solutions. In the experiment of GPS signal correction, the GPS signal accuracy was evaluated, and a linear interpolation method was developed to correct the inaccurate GPS data caused by the low GPS update frequency. After this correction, the GPS accuracy was limited by the intrinsic GPS signal deviation, which was around 10 meters. This GPS signal deviation limited the prediction accuracy of the BR-MLE algorithm. In the experiment of background radiation estimation, the background radiation distribution was estimated using a dataset containing eleven days worth of measurements from a single node. A data cleaning approach was also proposed to select measurements under the same background radiation shielding situation. With selected measurements, the radiation background distribution calculated by the BR-MLE algorithm identified high background radiation areas on the campus such as the Nuclear Radiation Laboratory. In the experiment of anomalous source detection, the BR-MLE based approach made accurate source alarms with lower false positive rates compared to the KSigma method. By using the information provided by the background radiation distribution, the BR-MLE based approach had better detectability than the KSigma based approach for low false positive rates.
5.2 Future Work

The mobile sensor networks showed their potential during the anomalous source detection experiments conducted for this thesis. In order to improve the detector network’s real-time processing capability, robustness, and detectability, several interesting topics could be pursued in the future.

Real-time Sensor Network

It was important to monitor an area’s radiation level and make alarms in real time. There were two aspects that needed to be considered for real-time processing: the data streaming and the online algorithm. The measurements should be able to be streamed in real time into a database for further analysis. The processing algorithm should be either an online algorithm that continually updates its alarm prediction once a new measurement had been acquired, or a high-speed batch algorithm that can be used to process large amounts of data in a short time. For both of these two aspects, cloud storage and computing should provide a possible solution. At the writing of this thesis, a real-time data streaming approach based on Amazon Web Service (AWS) was being developed. Early tests of this approach had streamed measurements from the D3s detectors into AWS S3 cloud storage in real time.

Data Cleaning Challenge

The data cleaning problem was another challenge in the application of sensor networks. Different sensor nodes had different working environments and different response functions. The quality of the output of a sensor network relied heavily on the calibration of the sensor network. The data selection was also an important step in the data cleaning process. This thesis used a smooth algorithm together with a threshold to select the measurements taken when the node carrier was walking. This work could also be done with machine learning methods such as clustering algorithms to capture the intrinsic clustering behaviors in the dataset.

Implementation of Background Radiation Distribution Information in Other Algorithms

As discussed in Chapter one, most of the current anomalous source detection algorithms assumed that the background radiation was uniformly distributed. It remains to be seen
whether the background radiation distribution can improve these algorithm’s performance or not.
REFERENCES


