DEPLOYMENT AND CHARACTERIZATION OF A ROBOTIC PLATFORM FOR RADIATION DETECTION

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ABSTRACT

This work centers around a state of the art gamma and neutron radiation detector, which is able to display radiation information about its surrounding at every second. Information about the count level is displayed along with the energy range of the detected radiation. Currently, similar sensors are only capable of passive radiation detection and function in stationary positions on the sides of highways, the entrances to buildings, and at major intersections.

The sensor has design considerations which allow it to move about and be more aggressive in its search. Its small size and low profile design allow it to be mounted on a robotic platform and search in small spaces such as underneath a car. Ultimately it would be able to autonomously localize an unknown number of dangerous radioactive sources, allowing workers to stay at a safe distance.

The sensor has been characterized using exempt Cs-137 and Co-60 gamma sources. A thorough profile was done of the measurements made by the sensor at varying distances with different combinations of radioisotopes present. Based on the findings, an algorithm was developed to scan an area similar to that of the wheelbase of a car and record the radiation levels. These measurements are used to localize from one to three radioactive sources.

1. INTRODUCTION

Few papers have been published concerning the autonomous detection and localization of radioactive sources; however a large number of papers are available that address the localization of isotropic sources in other contexts. The most common application involves the localization of acoustic sources [1], [2], [3], [4]. There are applications in many other areas but the energy based methods for acoustic source localization provided a starting point for the development of a method for autonomously localizing radioactive sources with a robotic platform.

2. RADIOACTIVE SOURCE MODEL

2.1. Model Description

An isotropic radiation source emits energy equally in all directions. The observed radiation at a given distance is inversely proportional to the square of the distance. The inverse square law means that as the distance increases linearly, the observed radiation decreases by the square. At a given sensor location the observed signal from a single radioactive source can be modeled by Equation (1).

$$s_i = g_i + e_i = \frac{k}{d^2} + e_i, \tag{1}$$

where g_i is the error free measurement, k is a positive constant, d is the distance from the source to the sensor, and e_i is the measurement error.

For the multiple source case the measurement taken at the *i*th sensor can be modeled by the sum of the individual source contributions as in Equation (2), where p_i and p_j denote the positions of the i^{th} sensor and the j^{th} source.

$$s_i = \sum_{j=1}^{J} \frac{k_j}{\| p_i - p_j \|^2} + e_i, \tag{2}$$

Radiation measurements taken at a given distance from a radioactive source look like samples drawn from a Poisson distribution [5]. The variance of a Poisson distribution is equal to its mean so the measurement noise and error will be quite small compared to the variation in the signal itself. This property of radiation sources allows Equation (2) to be rewritten as:

$$s_i = \sum_{j=1}^{J} \frac{k_j}{\| p_i - p_j \|^2}, \tag{3}$$

where the error term is ignored.

2.2. Testing of the Source Model

The radiation sensor used for the work described in this paper was made for the IRIS lab by Nucsafe Inc. It contains separate channels for neutron and gamma sensing. The work we performed involved only exempt gamma sources because of their relative safety and ease of procurement and use. The specific isotopes used were Co-60, five sources of one µCi, and Cs-137, two sources of ten µCi and two sources of five µCi.

In order to verify the accuracy of the model presented in Equation (3) and to determine the range of the sensor for our particular radioactive sources, we performed a series of characterization experiments. We placed individual sources at varying distances from the sensor and observed how well the data could be fit to Equation (3) by choosing the proper *k* parameter. As the length of the integration time for the measurement increases, so does the measurement accuracy. We chose an integration time of five seconds for data collection at each distance. The data collected for multiple trials with different types of sources yielded similar results. The sensor results were most accurate in the [0.2, 1.2] meter range for our particular radioisotopes. A typical experiment trial yielded data similar to that in Fig. 1 where the average error for each data point in the [0.2, 1.2] meter range was less than 7% from the predicted model value and the average error for each data point in the [.01, 2] meter range was less than 12%.

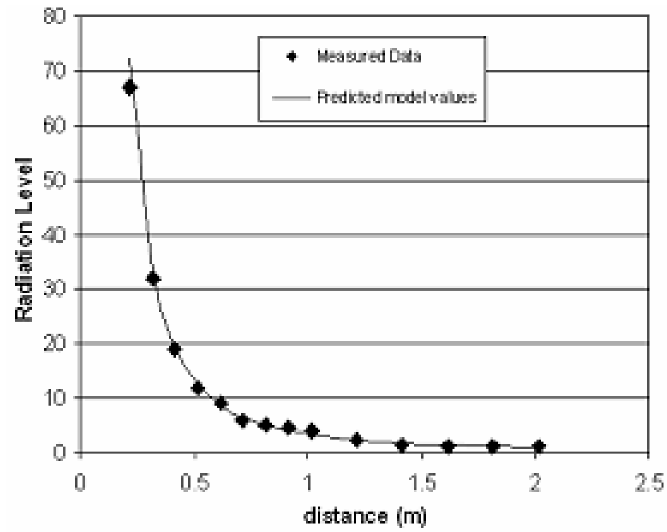

Fig 1. Test of Inverse Square Model with 10 µCi of Cs-137.

3. PROBLEM FORMULATION

Source localization using distributed networks has been actively examined for years. However, the cost of a state of the art gamma and neutron detector approaches $50,000 so it is not feasible to have distributed sensors for source localization. We will strive to develop a technique that is able to localize an unknown number of sources of unknown strengths based on the data collected from a scan with a single radioactive sensor.

The scan would only take place if the presence of radioactive material was first detected in the area being inspected. Since the scan would only be done on a limited basis, computation time is not a huge consideration, but nonetheless we attempt to develop an efficient technique that is not too computationally expensive or time exhaustive.

Iterative optimization techniques offer the best localization of sources, especially in the presence of noise or measurement fluctuation [6]. Closed form techniques often become trapped in local extremes or identify a false location because of reverberations in the environment [2]. Commonly used techniques such as estimating the direction of arrival or the time delay of arrival at different sources are hampered by scattering and reflections that can cause correlation errors [7].

The process of localizing a number of sources within an area is an inverse problem. Inverse problems can be classified into two types:

(1) Given the system characteristics, find the input that yields a measured output,
(2) Given the input and output, find the system characteristics that yield the given input-output pair [8].

Inverse problems are often ill posed problems as small changes in the input data can give rise to large fluctuations in the output. Most inverse problems are of the second type where the system is characterized. However, the source localization problem is a problem of causation. The problem is not ill posed because the system inputs are highly constrained. The sources are only allowed to be in a given area and they are limited to a small number of impulses in space [8]. These constraints are justified based on the fact that the main application for this technique is to localize a small number of sources within a space such as a transportation vehicle; car, truck, van, trailer, etc. which all have a given area and limited spaces in which to place radioactive sources.

A general approach to solving the inverse problem of source localization is to generate a set of forward problems that could have created the measured outputs given the system characteristics. The forward problem that minimizes an objective function or best fits the known system model is chosen to be the best one. The iterative generation of forward problems works best in environments such as a room or a vehicle that have well defined boundaries. Often iterative optimization techniques are more computationally expensive than the closed form techniques. However, they are more likely to find the true source location and are better able to do this in the presence of noise. An algorithm that performs well given a significant noise or variation in the data is especially important when localizing radioactive sources.

4. THE ITERATIVE SOURCE LOCALIZATION TECHNIQUE

4.1. Theory

For the general case where there are I sensor locations and J radioactive sources present, matrices can be written that allow for easy and compact representation of Equation (3). The radiation measurement at each sensor is given by:

$$S = \left[s_1 \; s_2 \; s_3 \; \ldots \; s_I\right]^T . \tag{4}$$

D contains the distances from every sensor location to each of the sources.

$$D = \begin{bmatrix} \frac{1}{{d_{11}}^2} & \frac{1}{{d_{12}}^2} & \frac{1}{{d_{13}}^2} & \cdots & \frac{1}{{d_{1J}}^2} \\ \frac{1}{{d_{21}}^2} & \frac{1}{{d_{22}}^2} & \frac{1}{{d_{23}}^2} & \cdots & \frac{1}{{d_{2J}}^2} \\ \frac{1}{{d_{31}}^2} & \frac{1}{{d_{32}}^2} & \frac{1}{{d_{33}}^2} & \cdots & \frac{1}{{d_{3J}}^2} \\ \vdots & \vdots & \vdots & \ddots & \\ \frac{1}{{d_{I1}}^2} & \frac{1}{{d_{I2}}^2} & \frac{1}{{d_{I3}}^2} & & \frac{1}{{d_{IJ}}^2} \end{bmatrix} \tag{5}$$

The matrix K contains the parameters specific for each source.

$$K = [k_1 \; k_2 \; k_3 \; \ldots \; k_J]^T , \tag{6}$$

Equation (3) can thenbe expressed compactly as:

$$S = DK . \tag{7}$$

This model is parameterized by the K matrix whose values vary depending on the radioisotopes and their strength. The individual k parameters control the decaying function that describes the amount of radiation observed from one source as the distance from that source is increased. Since the k parameters and the source strength are both unknown, an effective method for source localization can be developed based on a search for the locations in the region of interest where K best models the expected shapes.

The area where the sources are assumed to be located can be divided into a grid so there is a set of discrete points for the algorithm to use in attempting to localize the radiation sources. For two dimensional source localization each of these discrete points has an area of possible source location associated with it, and in three dimensions each point has a volume associated with it. By choosing a smaller grid spacing the resolution of the localization can be enhanced at the cost of added computation time.

For a chosen grid with a resolution of m points on the x axis, n points on the y axis, and o points on the z axis, there are $m \times n \times o$ number of points. However, for J number of sources we are interested in searching each unique combination of J points. The number of combinations can be found by adding the number of combinations of points that excludes repeated points to the combinations that only contain repeated points. Given J sources present in the area, the number of combinations to be searched is given by:

$$q = \frac{v!}{J!(v-J)!} + \left(v^J - \frac{v!}{(v-J)!} \right), \tag{8}$$

where $v=m*n*o$. We are interested in searching the combinations that contain repeated points because of the possibility of multiple sources located in the same area.

For each of these combinations of possible source locations K can be directly calculated for all the sensor locations where a measurement was taken using Equation (7). First, we must calculate the distances to the grid points from each of the sensor locations. For three dimensional source localization the distance from the i^{th} sensor to the possible locations of the sources can be calculated by

$$d_{ij} = \sqrt{(x_i - x_m)^2 + (y_i - y_n)^2 + (z_i - z_o)^2} , \tag{9}$$

and a similar distance calculation can be made in the two dimensional case.

For each combination of points, K will be calculated using the measurements from each of the sensor locations to perform a least square error fit. The result for each combination will be a vector containing the corresponding k parameters.

The error model for each combination will be defined as the sum of the square of the differences between the actual measurements and those predicted with the k parameters found with the least squares fit. The error equation can be written as

$$E_{(m,n,o)} = \sum \left[(S - DK) \cdot (S - DK) \right]. \tag{10}$$

This model essentially describes the validity of the curve fit, or the amount by which actual measurements vary from the generated curve. The combination of source locations with the least squares error is the best choice for the actual sources' locations. A simple search through the set of all combinations allows us to choose the one with the least error as the predicted combination of sources' locations.

4.2. The Three Source Case

When three radioactive sources are present, Equation (7) can be expressed as

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_I \end{bmatrix} = \begin{bmatrix} \frac{1}{d_{11}{}^2} & \frac{1}{d_{12}{}^2} & \frac{1}{d_{12}{}^2} \\ \frac{1}{d_{21}{}^2} & \frac{1}{d_{22}{}^2} & \frac{1}{d_{23}{}^2} \\ \frac{1}{d_{31}{}^2} & \frac{1}{d_{32}{}^2} & \frac{1}{d_{33}{}^2} \\ \vdots & \vdots & \vdots \\ \frac{1}{d_{I1}{}^2} & \frac{1}{d_{I2}{}^2} & \frac{1}{d_{I3}{}^2} \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix}. \tag{11}$$

The number of possible combinations to be searched to obtain the one location with the least error is given by:

$$q = v^3 - \left(\frac{5}{6} v (v-1)(v-2) \right). \tag{12}$$

4.3. The Two Source Case

For two sources, Equation (7) reduces to

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_I \end{bmatrix} = \begin{bmatrix} \frac{1}{d_{11}{}^2} & \frac{1}{d_{12}{}^2} \\ \frac{1}{d_{21}{}^2} & \frac{1}{d_{22}{}^2} \\ \frac{1}{d_{31}{}^2} & \frac{1}{d_{32}{}^2} \\ \vdots & \vdots \\ \frac{1}{d_{I1}{}^2} & \frac{1}{d_{I2}{}^2} \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \end{bmatrix}, \tag{13}$$

and the number of possible combinations to be searched to obtain the one with the least error is given by:

$$q = v^2 - \frac{v(v-1)}{2}. \tag{14}$$

4.4. The Single Source Case

If only one radioactive source is present, the model for the observed radiation at a given sensor reduces to its simplest form

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_I \end{bmatrix} = \begin{bmatrix} \frac{1}{d_{11}{}^2} \\ \frac{1}{d_{21}{}^2} \\ \frac{1}{d_{31}{}^2} \\ \vdots \\ \frac{1}{d_{I1}{}^2} \end{bmatrix} [k_1], \tag{15}$$

and the number of points to be searched is:

$$q = v. \tag{16}$$

5. ROBOTIC SENSOR MEASUREMENTS

The sensor was mounted on a wireless robotic platform and a number of different paths for the robot were considered based on the size and shape of the area to be scanned for radioactive material. A medium car has a rectangular shape with a width of approximately 1.5 – 2 meters and a length of a slightly over 3 meters. The first path considered was a circle. This path would keep the sensor a set distance away from the center of the area being scanned and give a desired symmetry to the measurements. Given the length of the car, 3 meters, the radius of the circle would have to be at least 1.5 meters. The characterization performed on the sensor being used showed a large degradation in the signal to noise ratio occurring between 1-1.3 meters for the radioactive sources tested. Therefore the circle path was discarded.

A rectangular path would keep the sensor closest to the edge of the area being scanned and minimize the distance to the sources. With a car width of slightly under 2 meters the sensor would be on the edge of its effectiveness with a rectangular shaped area.

The sensor was purposely designed with a low profile so that it could be coupled with a low profile robot and fit underneath a car. Therefore the path could also include a section underneath the car. This would decrease the distance at which the measurements would be made and most likely provide better data. However, it would also complicate the path slightly.

6. RESULTS

6.1. Results of Real Robot Measurements

We tested the algorithms presented above using the Safebot robot developed by the Imaging, Robotics, and Intelligent Systems Laboratory to perform autonomous collection of data. The results of the source localization algorithm and the gathered data are then sent wirelessly to a remote computer through a wireless network connection and visualized using the GUI of Figure 3. The Safebot is built to have a low profile so that it is able to fit into low spaces and is track driven so it is able so negotiate somewhat rough terrains.

Fig 2. Track driven Safebot robot with the radiation sensor mounted in the center.

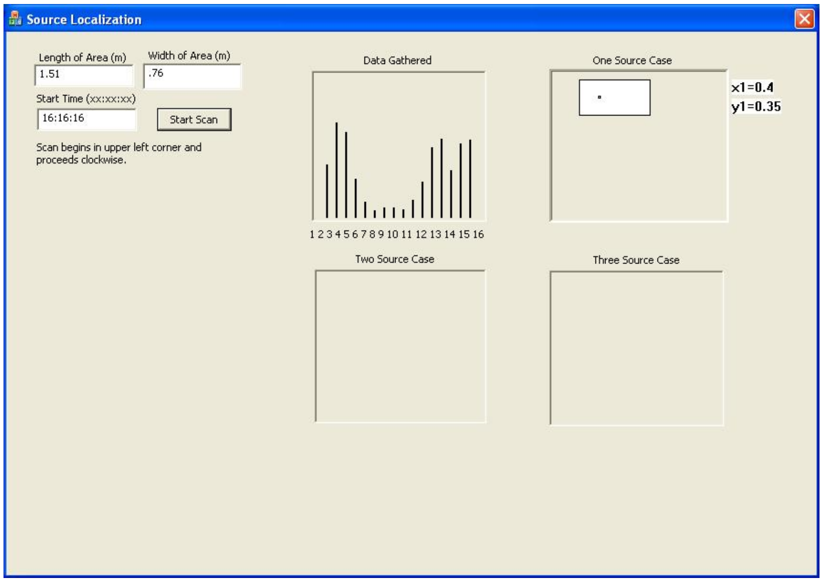

Fig 3. GUI developed for wireless control of the robot and for viewing of the gathered data and localization results.

We were only able to test the real robot configuration on a limited number of source combinations and placements because of practical considerations such as time and battery life. The data gathering by the robot demonstrated that autonomous source localization could be performed and the results viewed at a remote location.

In order to do more extensive testing of the performance of the source localization algorithms we generated a large amount of simulated data.

6.2. Results from Simulated Data

The simulated data was generated by randomly placing a combination of sources within a square area with a side dimension of one and a half meters. The distances could then be calculated from the positions of the sources to a previously determined set of sixteen measurement locations. The ideal measurement values could then be calculated using the radiation model shown in Equation (3). These ideal values were then treated as the mean of a Poisson distribution from which a measurement value was randomly taken. This data is a worst case data because no averaging of the data is done over time. The shortest data integration time that the sensor can perform is one second. A total of one thousand sources were localized for the one, two, and three source cases. The results can be seen in the histograms of Figures 4, 5, and 6 respectively for the cases of single, two, and three sources.

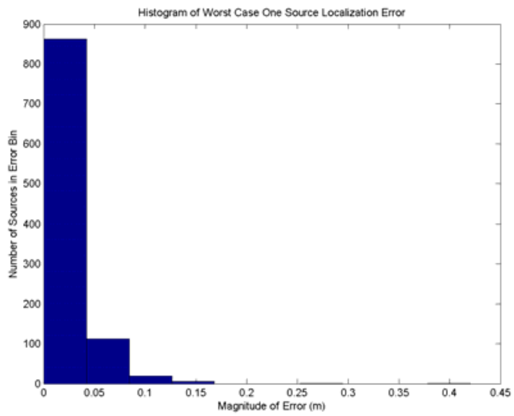

Fig 4: Histogram of error in meters for a single source localization

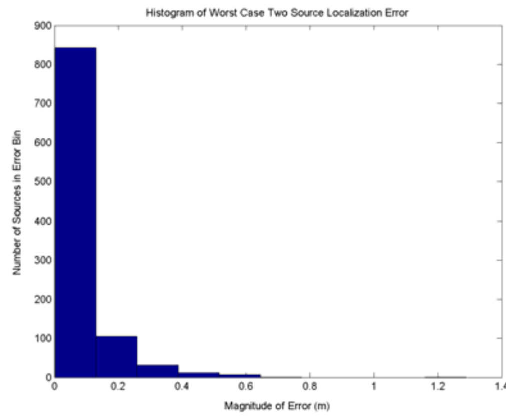

Fig 5: Histogram of error in meters for two source localization

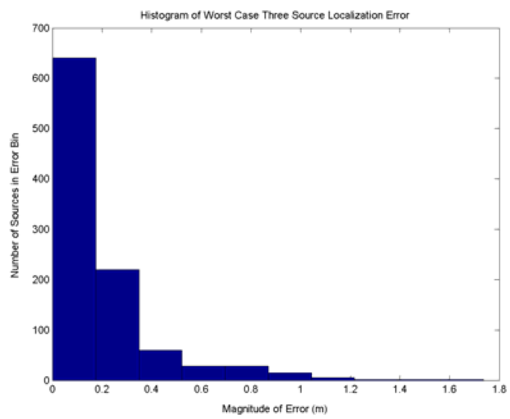

Fig 6: Histogram of error in meters for three source localization

The search resolution of the algorithm is decreased as the number of sources present increases. The search resolution for one source is .01 meters, for two sources it is .07 meters, and for three sources it is .15 meters. This saves computation time as the number of combinations to be computed is greatly decreased. The fluctuations in the measurement values due to each source are additive, so as the number of sources increases the data gets further and further away from the value predicted from the ideal model. The performance of the source localization degrades as more sources are added.

7. CONCLUSIONS AND CURRENT WORK

We have developed a method for radioactive source localization that allows a robot to perform the necessary data collection and human personnel to view the results of the data collection and the source localization at a safe distance over a wireless network. The method developed is effective for areas and sources for which the ratio of the area to source strength is small enough such that sufficient measurements can be made from the perimeter of the area.

Currently work is being done on other methods of localization in which the robot traverses the interior of the area in question. This allows the robot to travel directly to the source and transmit an energy map wirelessly based on its GPS coordinates. One method currently being worked on involves the robot making a series of concentric circles during which data is gathered. Based on the measurements made, a vector is picked that is most likely to lead to the source of the radiation. If a decline or leveling off of the observed radiation occurs while traveling along that path the robot is able to re-vector itself with another set of concentric circles.

Acknowledgments
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hadron collider Light detection and ranging European Platform on preparedness for nuclear and radiological emergency. 7.Â The group looks at issues such as certification of radiation detectors, standardisation of deployment protocols, response procedures and communication to the public, for example in the event of criminal or unauthorised acts involving nuclear or other radioactive material out of regulatory control.Â Our organisation uses a robot platform in laboratory experiments for transportation of our. detector SENNA (detection of explosives and radioactive sources) to suspicious objects.Â â€¢ Radiological monitoring and control, characterisation of contaminated areas, decommissioning and dismantlement of contaminated buildings/structures. . . This discussion is targeted at the robotics or remote systems professional who is interested in using his or her commercial system in a nuclear application or who is beginning the design of a new system for deploying in a nuclear environment, and for those who are interested in robotics and remote systems in nuclear environments. This person will need to have an understanding of the expected levels of radiation and radiation dose rates that might be encountered in these environments. A typical robotics/remote systems engineer will be unfamiliar with nuclear applications, as many engineers come from a very diverse set of backgrounds typically found in the robotics arena; namely, mechanical engineering, electrical engineering, and computer science. We describe a prototype robotic monitoring platformâ€"the RhizoChamber-Monitor for analyzing growth patterns of plant roots automatically. The RhizoChamber-Monitor comprises an automatic imaging system for acquiring sequential images of roots which grow on a cloth substrate in custom rhizoboxes, an automatic irrigation system and a flexible shading arrangement.Â In the field, in vivo root tracing usually involves the transparent surface of a buried minirhizotron with a cylindered imaging sensor or a buried optical flat-bed scanning system [4, 5]. However, only a very small proportion of the whole root system is visible through such a transparent surface.