Kayla Grieme was born and raised in Memphis, TN. She will graduate from The University of Memphis with Honors in Spring of 2015 with a Bachelors of Science degree in Computer Science. She has always loved computer science, especially data mining, data fusion, and sensor networking. Her other interests include fitness, choir, St. Jude Children's Research Hospital, and music of all kinds. She loves Memphis and will soon begin her graduate degree in Fall of 2015 at The University of Memphis. This author was awarded second place prize for best paper.

Kayla Grieme

On a Triangulation-Based Approach to Radiation Source Detection

Faculty Sponsor
Dr. Chase Q. Wu

Abstract

Among many terrorism threats faced by our nation, the release of radiation at a low but dangerous level in densely populated areas is probably one of the most horrifying and devastating attacks. Unfortunately, detecting low-level radiation sources is difficult due to varied background noise and probabilistic measurements with inherent randomness. Significant efforts have been made using single or co-located sensors, but have only met with limited success. The recent advance in sensing technology has now made it possible to deploy a large number of smaller and less expensive detectors to achieve quality through quantity. Such networks of detectors are expected to provide faster detection with higher accuracy than their constituent detectors. We propose a triangulation-based data fusion method for radiation source detection using a network of distributed detectors through rigorous algorithm design and analysis. The performance superiority of our method is demonstrated by extensive experimental results in comparison with existing methods.

Introduction

The release of radiation at low but dangerous levels in densely populated areas is considered to be potentially horrifying and devastating. Unfortunately, detecting low-level radiation sources is extremely challenging because i) the radiation levels that are only slightly above the background noise may appear to be normal background variations; and ii) the radiation measurements are probabilistic in nature with inherent randomness, typically following Poisson process. In the past decades, many analytical or experimental methods have been developed using single or co-located sensors, but these efforts have only yielded limited success.

The recent advance in microelectronics and sensing technology has now made it possible to deploy a large number of smaller and less expensive detectors, resulting in an achievement of quality through quantity in practical monitoring applications involving urban areas, special events, and border crossings. In general, a large-scale sensor deployment would cover a wide geographical area and hence result in a large collection of sensor data, but the speed and accuracy of detection still largely depends on the underlying method used to fuse or integrate the sensor data. Research efforts on the design of such data fusion algorithms are still quite limited, especially in the domain of radiation source detection.

In this work, we propose a triangulation-based data fusion method for radiation source detection, referred to as TriRSD, using a network of distributed detectors through rigorous algorithm design and analysis. One salient feature of TriRSD is that it makes a detection decision based on the source location estimate, which is obtained by solving a system of equations using a closed form. This localization-based detection method is in sharp contrast to conventional "detect first and then localize" approaches employed for radiation source detection. Indeed, localization by the network has an inherent advantage over individual detectors. With multiple estimates of the source location generated based on the measurements from the subnets, or groups of sensors, if a source is present, these estimated locations would form a single dominant cluster; otherwise, they would be dispersed. This property is exploited in TriRSD to improve the detection performance of individual detectors. The performance superiority of TriRSD is demonstrated by extensive experimental results in comparison with Sequential Probability Ratio Test (SPRT), a widely adopted method for radiation source detection.

Related Work

A detection algorithm infers the presence or absence of a radiation source given sensor measurements from single or multiple sensors. The general detection problems have been studied extensively over the past several decades, and include areas of classification, estimation, identification, and tracking, under various formulations.

Detection of radiation sources is typically accomplished by looking for sensor measurements that are dissimilar to the background radiation profile. In absence of noise and measurement errors, this can be done by triggering a detection alarm when sensor measurements differ from the background radiation profile. However, in a realistic setting, the variation in the sensor measurements may be due to a statistical variation of the intensity, or changes in the background radiation profile. According to extant literature, many methods have been developed for radiation source detection in different problem spaces according to the number of sources, i.e., single or multiple sources, and the state of sensors, i.e., static or moving sensors.

Fehlau proposed a time-smoothing filter technique and compared different detection methods using an exponential smoothing filter and amoving average filter. The detection method in [2] and [3] is based on a geometric model of the time difference of arrival (TDOA). Many other detection methods use statistical techniques, including Maximum Likelihood Estimation (MLE) [4], [5], [6], [7], [8], [9], [10], [11], [12], Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) [13], [14], Bayesian Estimation [15] [16] [17] [18], Grid methods [19] and Particle Filters [20]. As one of the most commonly used methods, the Sequential Probability Ratio Test (SPRT) employs a recursive hypothesis testing method to decide on two hypotheses given a series of sensor measurements [21],[22],[23],[24],[25].

In contrast with the traditional detection methods mentioned above, the proposed TriRSD takes a novel approach to first derive the source location by fusing the data from a subset of sensors and then making a detection decision based on the clustering of source estimates.

TriRSD: Triangulation-based Radiation Source Detection

We propose a triangulation-based method for Radiation Source Detection, referred to as TriRSD. This method is intended for detecting all levels of radiation, although it becomes more effective as the level of radiation increases and the background noise decreases. The principle idea [1] of this method is to compute the source location by solving a system of nonlinear equations based on a d^2 signal attenuation model using three sensors that form a triangle, as follows:

$$\begin{cases} \dfrac{A}{d_1^{\,2}} = \dfrac{A}{(x-x_1)^2+(y-y_1)^2} & = m_1(t), \\ \dfrac{A}{d_2^{\,2}} = \dfrac{A}{(x-x_2)^2+(y-y_2)^2} & = m_2(t), \\ \dfrac{A}{d_3^{\,2}} = \dfrac{A}{(x-x_3)^2+(y-y_3)^2} & = m_3(t), \end{cases} \quad \text{or} \quad \begin{cases} A & = d_1^{\,2} \cdot m_1(t), \\ A & = d_2^{\,2} \cdot m_2(t), \\ A & = d_3^{\,2} \cdot m_3(t), \end{cases}$$

As shown here, $m_i(t)$ and (x_i, y_i) are the count (sensor reading) at time t and the location of the i-th sensor (=1, 2, 3), which are known; A and (x, y) are the intensity and the location of the radiation source, which are to be solved, and d_i is the Euclidean distance between the source and the i-th sensor, i.e. $d_i = \sqrt{(x-x_i)^2+(y-y_i)^2}$. Note that this d^2 attenuation model has been validated using real radiation measurements and could be used for an accurate estimate of radiation attenuation in real-life application scenarios.

Theoretically, with an accurate model and perfect measurements, if there is no source present, the computed or estimated source location $(\hat{x}, \hat{y})$ would be the centroid of the corresponding triangle; otherwise, it would be the actual source location (x, y). In practice, with an inaccurate model and imperfect measurements (caused by randomness in the noise and signal), if a radiation source exists, the solutions from different triangles are expected to appear in close proximity and form a compact cluster (possibly around the actual source location). Therefore, we may measure the level of compactness of the cluster and compare it with a threshold to make a detection decision.

Algorithm 1 TriRSD (n, g, cct, l, t)

n: the total number of sensors
g: the percentage of sensors being considered for detection
cct: a given cluster compactness threshold
l: the number of triangles constructed
t: the current time

$m = n \cdot g$;
Choose m sensors with the strongest accumulated signal (counts) up to the current time t;
Construct a set of l triangles, each using 3 sensors randomly selected from the top m sensors;
for each triangle **do**
  Solve the equation system (triangle) in Eq. 2 for an estimated source location $(\hat{x}, \hat{y})$ using a closed-form method;
  if $(\hat{x}, \hat{y})$ is an imaginary solution **then**
    Ignore $(\hat{x}, \hat{y})$;
  end if
end for
Calculate the center $(\bar{x}, \bar{y})$ of the cluster as the average source location among all the real estimated source locations $(\hat{x}, \hat{y})$;
Calculate the distance $\hat{d}$ between each estimated source location $(\hat{x}, \hat{y})$ and the cluster center $(\bar{x}, \bar{y})$, i.e. $\hat{d} = \sqrt{(\hat{x} - \bar{x})^2 + (\hat{y} - \bar{y})^2}$;
Calculate the cluster compactness cc as the standard deviation σ of all the distances $\hat{d}$, i.e. $cc = \sigma = \sqrt{\frac{\sum_{i=1}^{r} (\hat{d}_i - \bar{d})^2}{r}}$, where r is the number of real estimated source locations, and $\bar{d}$ is the mean value of all the distances $\hat{d}$;
if $cc \leq cct$ **then**
  Claim a source detected;
else
  Claim no source detected;
end if

Figure 1.

The key steps of TriRSD are described in Alg. 1. Since the detection performance of TriRSD relies on the "quality" of constructed triangles, we only consider a subset (controlled by the percentage g) of sensors with the strongest signal (the highest count). If the number m of sensors being considered for detection is small, we may simply exhaust all the combinations of triangles, i.e. $l = C_m^3$. There are two main issues in solving the equation system of a triangle:

- Imaginary roots: imaginary roots do not contribute to the estimated location, and hence are simply ignored.
- Two real roots: a quadratic equation may produce two real roots, one of which is considered as a "true" solution while the other is considered as a "phantom" solution.

Note that "true" solutions are likely to form a cluster, but "phantom" solutions may be scattered as outliers. However, at the time of solving the equation, there is no sufficient information to discern whether a solution is "true" or "phantom". Therefore, we apply an outlier detection method before making a detection decision based on the compactness of the cluster.

Outlier Detection

Outlier detection is a technique in statistics, which is largely used for data mining. There are three commonly used methods for outlier detection [1]: 1) statistical distribution-based outlier detection, 2) distance-based outlier detection, and 3) density-based local outlier detection, which is employed in our work.

For the sake of completeness, we provide a brief introduction to the density-based local outlier detection method. We first define several terms as follows.

Definition 1: k -distance: the k -distance of an object p, denoted as k -distance (p), is the maximal distance from p to its k -nearest neighbors.

Definition 2: k -distance neighborhood: the k -distance neighborhood of an object p, denoted as $N_{k\text{-distance}(p)}(p)$ or $N_k(p)$ for short, contains every object whose distance to p is not greater than k -distance(p).

Definition 3: Reachability distance: the reachability distance of an object p with respect to object o (o is among the k -nearest neighbors of p), is defined as $\mathrm{ReachDist}_k(p,o) = \max\{k\text{-distance}(o), d(p,o)\}$, where $d(p, o)$ denotes the Euclidean distance between p and o.

Based on the above definitions, we further define the local reachability density (LRD) as:

$$LRD_k(p) = \frac{|N_k(p)|}{\sum_{o \in N_k(p)} \text{ReachDist}_k(p,o)},$$

and we use the following to calculate the local outlier factor (LOF) to decide if a data point (object) p is an outlier:

$$LOF_k(p) = \frac{\sum_{o \in N_k(p)} \frac{LRD_k(o)}{LRD_k(p)}}{|N_k(p)|}.$$

According to the above definition, $LOF_k(p)$ should be close to 1 if an object p is not a local outlier. Generally, the larger $LOF_k(p)$ is, the more likely p is a local outlier.

In TriRSD, to avoid introducing an additional threshold for outlier detection, we incorporate $LOF_k(p)$ into the calculation of the standard deviation σ of all the distances between the estimated source locations and the cluster center (Line 12 in Alg. 1) as a weight coefficient, i.e.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{r} LOF_k(p_i) \cdot (\hat{d}_i - \bar{d})^2}{\sum_{i=1}^{r} LOF_k(p_i)}},$$

where p denotes the i -th estimated source location $(\hat{x}, \hat{y})$, and the value of k is typically chosen within the range $[\frac{r}{4}, \frac{r}{2}]$.

Performance Evaluation

To evaluate the performance of TriRSD, we utilize the datasets from Domestic Nuclear Detection Office's (DNDO) Intelligence Radiation Sensors Systems (IRSS) tests, wherein 17 detectors were arranged in two concentric circles and a spiral. In each run, the first 60 seconds had the background measurements, and the source was present during the next 120 seconds.

Effect of Outlier Detection

To evaluate how effectively the outlier detection method improves the detection performance of TriRSD, we apply TriRSD with and without outlier detection to the IRSS dataset and plot the standard deviation of distances, as shown in Figures 2 and 3.

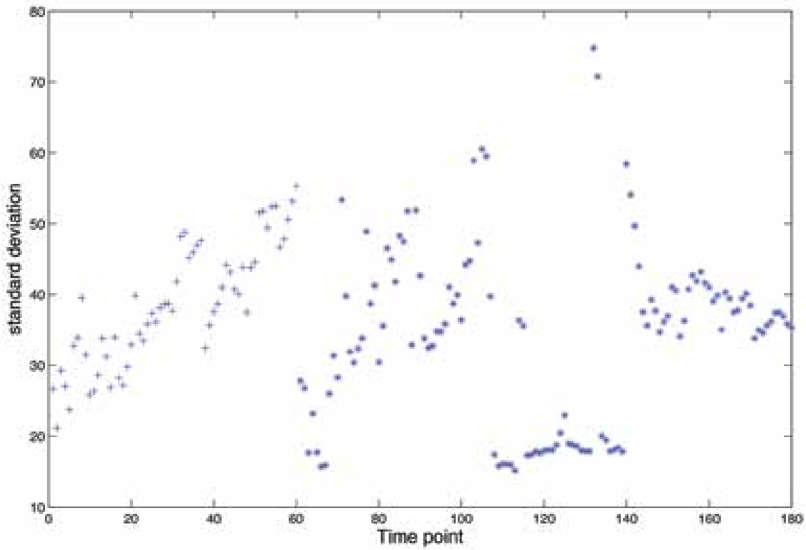

Figure 2.

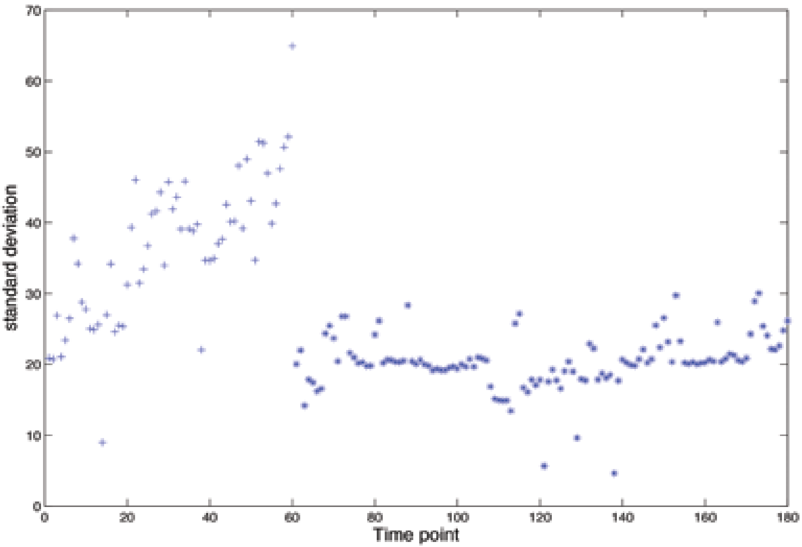

Figure 3. The distribution of standard deviations of distances over time. Fig. 2: before using outlier detection, Fig. 3: after using outlier detection. The symbol “+” represents the standard deviation in the first 60 seconds and the symbol “*” represents the standard deviation in the last 120 seconds. x -axis is the time point, and y -axis is the calculated standard deviation.

Without outlier detection, it is rather difficult to decide a meaningful cluster compactness threshold for source detection; but with outlier detection, we are able to choose an appropriate threshold (a horizontal line) that divides the standard deviations between the first minute (marked by "+") and the last 120 seconds or 2 minutes (marked by "*").

Performance Comparison

We run both the proposed TriRSD method and SPRT in comparison on multiple runs of the IRSS datasets. Since SPRT is very sensitive to its parameters, we calculate and apply the average measured intensity of signal and noise to improve its performance. False alarm rate is the percentage of runs which provide a false positive decision. Missed detection rate is the percentage of runs which provide a false negative decision and miss the source. We tabulate the false alarm rate and missed detection rate of both methods in multiple runs in Table 1, which shows that TriRSD exhibits an overall better detection performance than SPRT. The results in other runs are qualitatively similar.

Table 1. The detection performance of SPRT and TriRSD.

Performance measurements / Runs	False alarm rate (%)		Missed detection rate (%)	
	SPRT	*TriRSD*	*SPRT*	*TriRSD*
Run 1	0	1.6	25	1.6
Run 2	0	1.6	9.2	0
Run 3	0	1.6	29.2	0
Run 4	0	1.6	14.2	5.8
Run 5	0	1.6	15	1.6
Run 6	0	1.6	6.7	0.8

A Visual Illustration of TriRSD Detection Process

We provide a visual illustration of the detection process of TriRSD on one typical run. Figures 4, 5, and 6 show the layout of the estimated source locations at 6 different time steps in the first minute, at the first 6 time steps in the last 2 minutes, and at 6 different time steps in the rest of the last 2 minutes, respectively. We observe that the estimated source locations converge to the true source location (the origin) as more counts are accumulated over time.

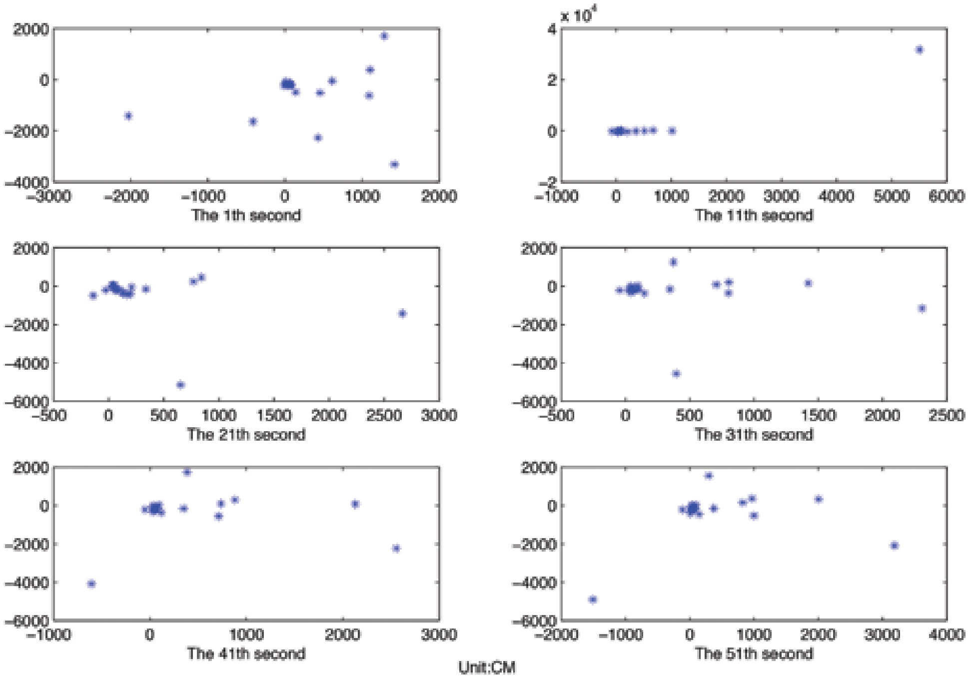

Figure 4. The layout of the estimated source locations at 6 different time steps in the first minute.

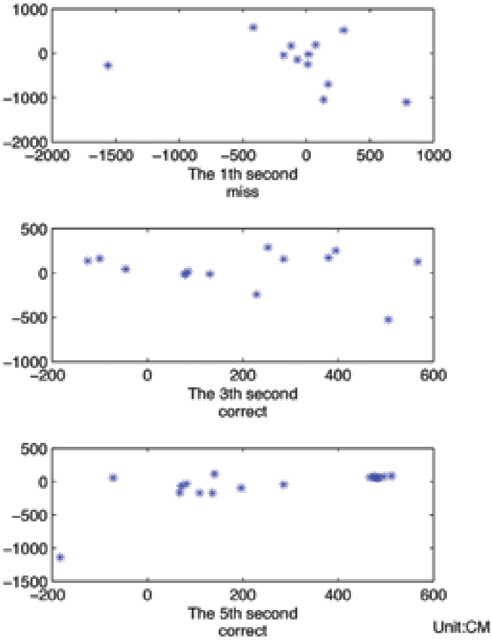

Figure 5. The layout of the estimated source locations at the first 6 time steps in the last 2 minutes.

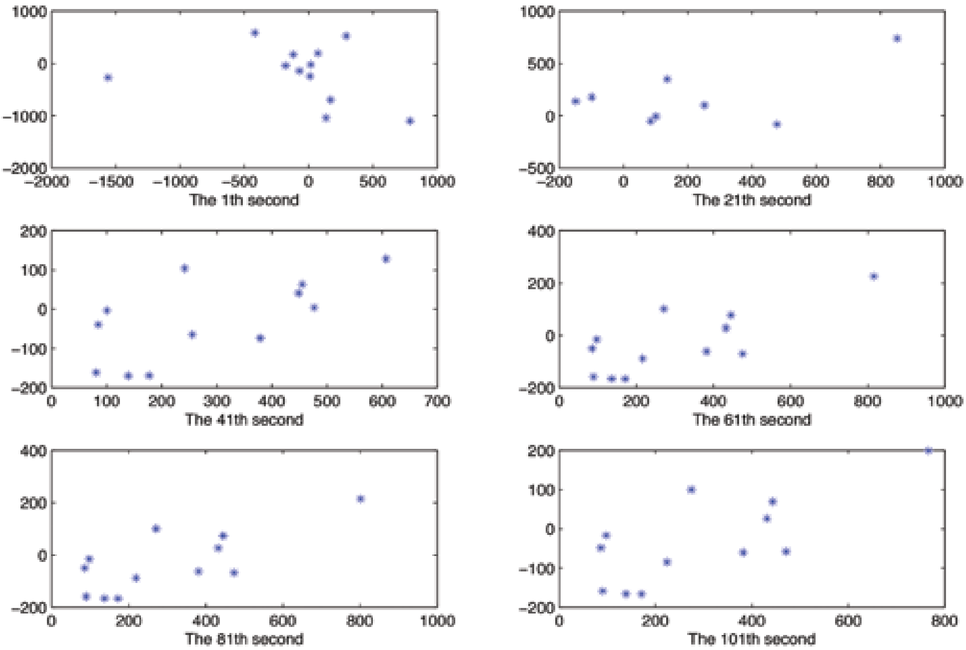

Figure 6. The layout of the estimated source locations at 6 different time steps in the rest of the last 2 minutes

Performance Impact of Threshold

To investigate the impact of the cluster compactness threshold on the detection performance of TriRSD, we vary the threshold value in the range from 10 to 28, and plot the corresponding false alarm rate and missed detection rate, as shown in Fig. 7. We observe that the best detection performance with both rates less than 5% is achieved with a threshold around 19.2 cm.

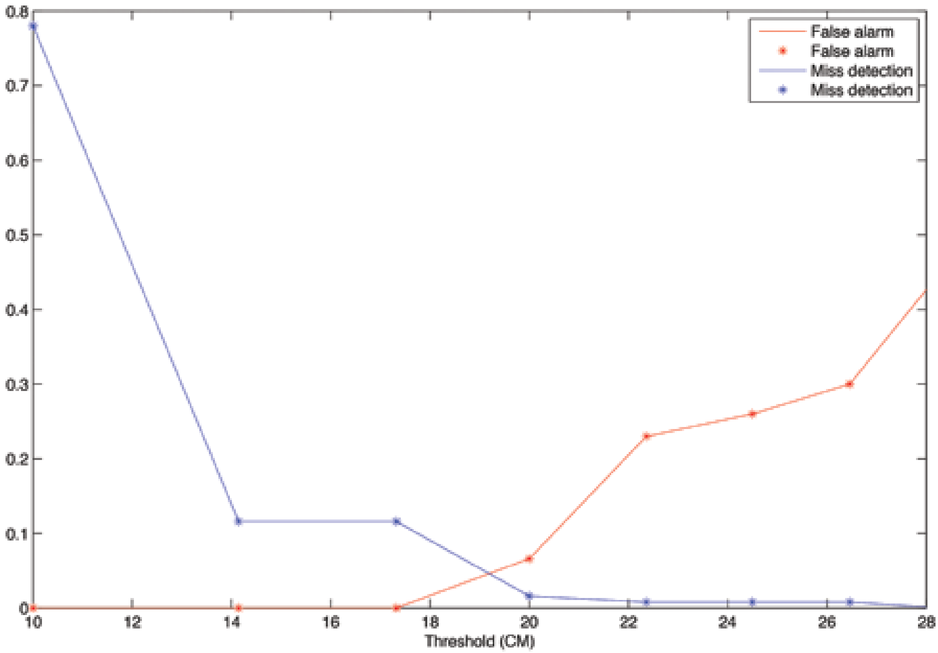

Figure 7. The impact of the threshold on the detection performance of TriRSD.

Conclusion

Detection of low-level radiation sources is an important but challenging problem. Detecting high-level radiation is easy, but it becomes much more difficult when detecting low-level radiation due to measurements of background noise. Unlike traditional geometrical or statistical approaches, we proposed a triangulation-based method for radiation source detection by estimating the source location using a rigorous closed-form solution. Extensive experimental results confirmed the performance superiority of the proposed TriRSD method over existing methods. These results will help expand the way security systems are implemented in public settings.

References

[1] P. E. Fehlau, “Comparing a recursive digital filter with the moving average and sequential probability-ratio detection methods for SNM portal monitors,” IEEE Transactions on Nuclear Science, vol. 40, no. 2, pp. 143–146, April 1993.
[2] X. Cheng, A. Thaeler, G. Xue, and D. Chen, “TPS: A time-based positioning scheme for outdoor wireless sensor networks,” in Proceedings of the 23rd IEEE International Conference on Computer Communications (INFOCOM), vol. 4, March 2004, pp. 2685–2696.
[3] A. Thaeler, M. Ding, and X. Cheng, “iTPS: An improved location discovery scheme for sensor networks with long-range beacons,” Journal of Parallel and Distributed Computing, vol. 65, no. 2, pp. 98–106, 2005.
[4] A. Gunatilaka, B. Ristic, A. Skvortsov, and M. Morelande, “Parameter estimation of a continuous chemical plume source,” in Proceedings of the 11th IEEE International Conference on Information Fusion (FUSION), June 2008.
[5] J. C. Chen, R. E. Hudson, and K. Yao, “Maximum-likelihood source localization and unknown sensor location estimation for wideband signals in the near-field,” IEEE Transactions on Signal Processing, vol. 50, no. 8, pp. 1843–1854, August 2002.
[6] X. Sheng and Y. H. Hu, “Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks,” IEEE Transactions on Signal Processing, vol. 53, no. 1, January 2005.
[7] M. R. Morelande, B. Moran, and M. Brazil, “Bayesian node localization in wireless sensor networks,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March 2008, pp. 2545–2548.
[8] W. Xia and Z. He, “Multiple-target localization and estimation of MIMO radars with unknown transmitted signals,” in IEEE International Symposium on Circuits and Systems (ISCAS), May 2008, pp. 3009–3012.
[9] M. Morelande, B. Ristic, and A. Gunatilaka, “Detection and parameter estimation of multiple radioactive sources,” in Proceedings of the IEEE 10th International Conference on Information Fusion (FUSION), July 2007.

[10] M. Ding and X. Cheng, “Fault tolerant target tracking in sensor networks,” in Proceedings of the 10th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc), 2009, pp. 125–134.
[11] C. Kreucher, K. Kastella, and A. O. Hero, “Multitarget tracking using the joint multitarget probability density,” Proceedings of IEEE Transactions on Aerospace and Electronic Systems, vol. 41, no. 4, pp. 1396–1414, October 2005.
[12] R. Vilim, R. Klann, S. de la Barrera, P. Vilim, and I. Ross, “Tracking of weak radioactive sources in crowded venues,” in IEEE Nuclear Science Symposium Conference Record (NSS/MIC), October 2009, pp. 995–1001.
[13] H. Akaike, “Information theory and an extension of the maximum likelihood principle,” in Proceedings of the 2nd International Symposium on Information Theory, 1973.
[14] G. Schwarz, “Estimating the dimension of a model,” The Annals of Statistics, vol. 6, no. 2, pp. 461–464, 1978.
[15] S. Brennan, A. Mielke, and D. Torney. Radioactive source detection by sensor networks. Nuclear Science, IEEE Transactions on, 52(3):813 – 819, 2005.
[16] M. Morelande and B. Ristic. Radiological source detection and localisation using Bayesian techniques. IEEE Transactions on Signal Processing, vol. 57 no.11, pp. 4220–4231, 2009.
[17] B. Ristic, M. Morelande, and A. Gunatilaka, “Information driven search for point sources of gamma radiation,” ACM Signal Processing, vol. 90, no. 4, pp. 1225–1239, 2010.
[18] M. R. Morelande, C. M. Kreucher, and K. Kastella, “A Bayesian approach to multiple target detection and tracking,” IEEE Transactions on Signal Processing, vol. 55, no. 5, pp. 1589–1604, May 2007.
[19] Y. Cheng and T. Singh, “Source term estimation using convex optimization,” in Proceedings of the 11th International Conference on Information Fusion (FUSION), June 2008.
[20] C. Kreucher, M. Morelande, K. Kastella, and A. O. Hero, “Particle filtering for multitarget detection and tracking,” in Proceedings of IEEE Aerospace Conference, March 2005, pp. 2101–2116.
[21] K. D. Jarman, L. E. Smith, and D. K. Carlson, “Sequential probability ratio test for long-term radiation monitoring,” IEEE Transactions on Nuclear Science, vol. 51, no. 4, pp. 1662–1666, August 2004.
[22] K. E. Nelson, J. D. Valentine, and B. R. Beauchamp, “Radiation

detection method and system using the sequential probability ratio test," 2007, U.S. Patent 7,244,930 B2.
[23] J.-C. Chin, "Efficient and robust solutions for sensor network detection and localization," Ph.D. dissertation, Purdue University, August 2010.
[24] N. S. V. Rao, C. W. Glover, M. Shankar, J. C. Chin, D. K. Y. Yau, C. Y. T. Ma, Y. Yang, and S. Sahni, "Improved SPRT detection using localization with application to radiation sources," in Proceedings of the IEEE 12th International Conference on Information Fusion (FUSION), July 2009.
[25] N. S. V. Rao, J. C. Chin, D. K. Y. Yau, and C. Y. T. Ma, "Localization leads to improved distributed detection under non-smooth distributions," in Proceedings of the IEEE 13th International Conference on Information Fusion (FUSION), 2013.