Urban Source Detection with Mobile Sensor Networks Enhanced with Machine Learning Algorithms

Z. Liu, and C.J. Sullivan

Department of Nuclear, Plasma, and Radiological Engineering, University of Illinois at Urbana-Champaign

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Abstract

Mobile radiation sensor networks integrated with global positioning system coordinates provide an attractive option for the task of dynamically monitoring a region's background radiation and detecting the illicit movement of radioactive materials. It is important to estimate anomalous sources' position and location accurately. Both statistical and probabilistic approaches have been developed for stationary sensor networks to estimate source parameters. Due to the limitation of computation complexity, most of these algorithms assume background radiation is uniformly distributed and constant. These algorithms have low efficiency to solve multi-source problems. In our previous work, an algorithm called the BR-MLE algorithm was developed for mobile sensor networks to estimate the spatial and temporal distribution of background radiation. Following that work, a pre-filter framework for mobile sensor networks is presented in this paper that estimates multiple sources' positions and intensity under the fluctuating background radiation. The pre-filter framework combines the BR-MLE algorithm, a clustering algorithm, and a traditional maximum likelihood estimation algorithm together, and decomposes the computation intensive multi-source estimation problem into several single-source estimation problems. This offers an efficient alternative to traditional approaches where the multi-source problems are difficult to solve and the background radiation distribution is not considered.

Problem Setup

- Radioactive Sources: $S = \{\alpha_1, \beta_1, \mu_1, \alpha_2, \beta_2, \mu_2 \;\dots\dots\; \alpha_n, \beta_n, \mu_n\}$

  Position of source j: (α_j, β_j), intensity of source j: μ_j
- Measurements: $M = \{x_1, y_1, c_1, x_2, y_2, c_2 \;\dots\dots\; x_m, y_m, c_m\}$

  Position of measurement i: (x_i, y_i), value of measurement i: c_i
- For measurement i:

$$\mathbb{P}(c_i) = \frac{\lambda_i^{c_i} e^{-\lambda_i}}{c_i!}, \quad \lambda_i = \sum_{j=1}^{n} \frac{\mu_j}{(x_i-\alpha_j)^2+(y_i-\beta_j)^2} + \lambda_b,$$

$$\textit{where } \lambda_b \textit{ is the background radiation intensity.}$$

- Goal: Estimate source parameter set S from measurement set M, including number of sources, and their position/intensity.

Workflow of pre-filter framework

- **Radial basis function (RBF) fitting:**

Generate $R(x,y)$, a smooth estimation[1] of radiation distribution, based on measurement set M:

$$R(x,y) = \sum_{i=1}^{m} w_i \cdot \varphi_i(x,y).$$

$\varphi_i(x,y)$ is a distance measure between (x_i, y_i) and (x,y), and w_i are the weights that solve the following equation:

$$\begin{bmatrix} \varphi_1(x_1,y_1) & \cdots & \varphi_m(x_1,y_1) \\ \vdots & \ddots & \vdots \\ \varphi_1(x_m,y_m) & \cdots & \varphi_m(x_m,y_m) \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix} = \begin{bmatrix} c_1 \\ \vdots \\ c_m \end{bmatrix}$$

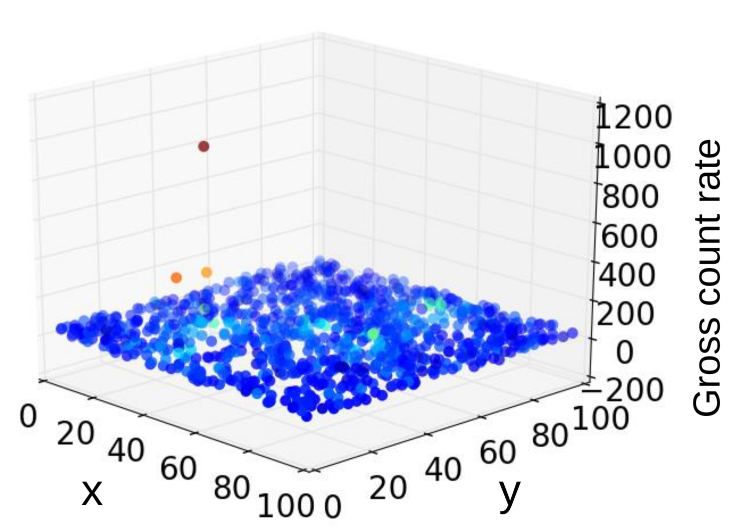

Figure 1: Measurements before RBF fitting.

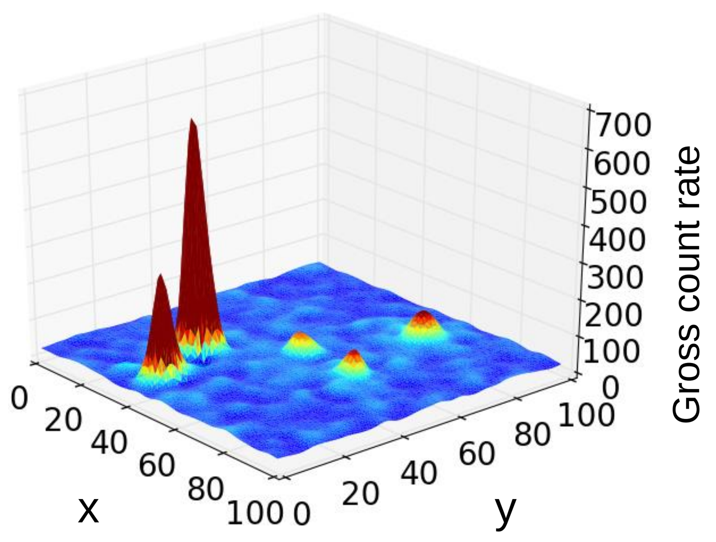

Figure 2: Approximated radiation distribution after RBF fitting.

- **Watershed Algorithm**

Segment an image into sub-regions such that each sub-region has only one peak[2]. There are 5 true sources in Figure 3.

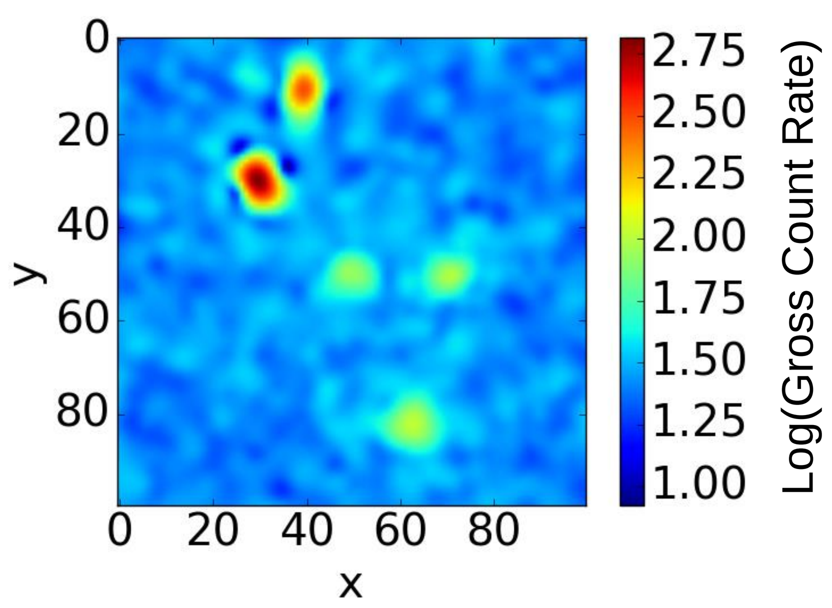

Figure 3: Approximated radiation distribution before segmentation.

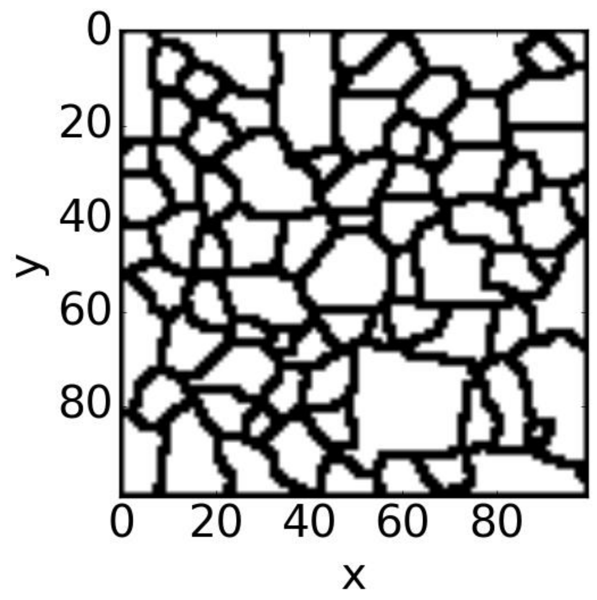

Figure 4: Segmentations of experimental area.

Workflow of pre-filter framework (Continued)

- **Clustering on peak parameters**

Find each sub-region's peak altitude and peak prominence, and run a DBSCAN algorithm based on those peak parameters to cluster sub-regions into non-source areas and source areas.

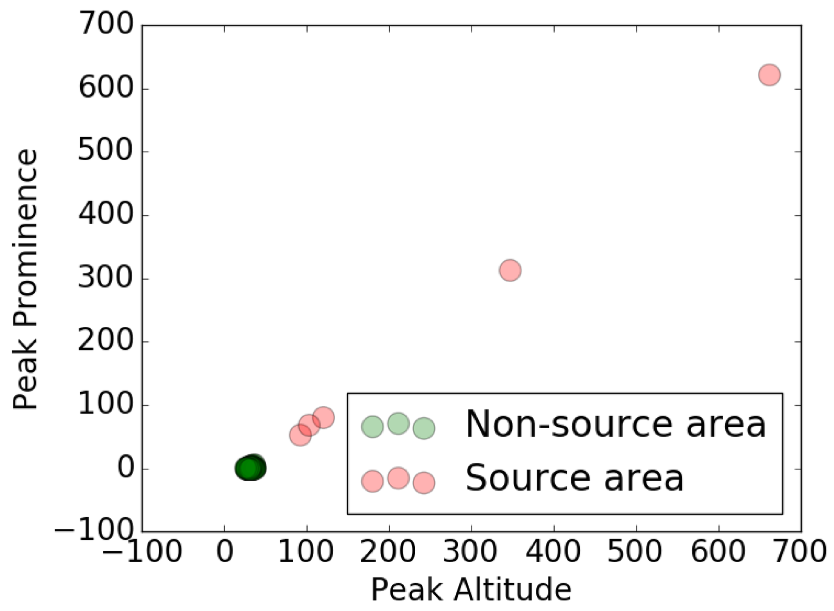

Figure 5: DBSCAN result of clustering on peak parameters.

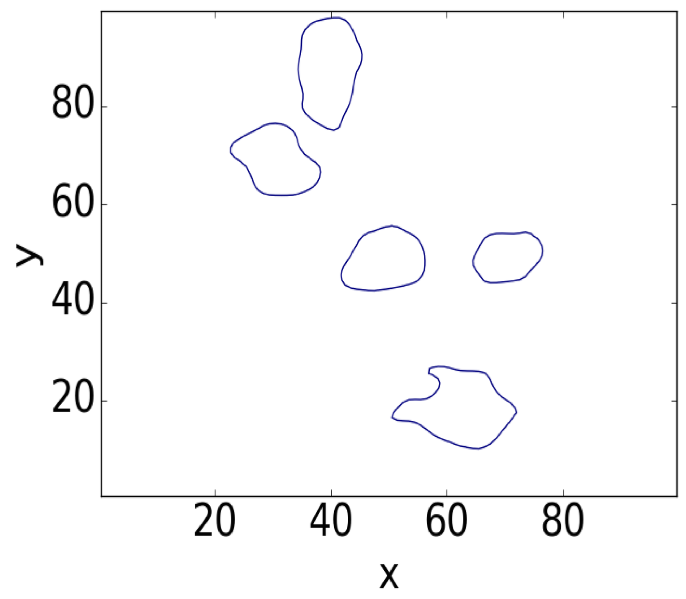

Figure 6: Identified source areas.

- **Maximum Likelihood Estimation**

Use Fisher's scoring algorithm[3] to solve the maximum likelihood estimation problem. Initial conditions are source areas' peak position and altitude obtained in the previous step.

$$l(S) = \mathbb{P}(M|S) = \sum_{i=1}^{m} c_i \cdot \log(\lambda_i) - \lambda_i$$

$$J(S_n) = \frac{\partial l(S_n)}{\partial S}, \qquad I(S_n) = -E\left[\frac{\partial^2 l(S_n)}{\partial S^2}\right]$$

$$S_{n+1} = S_n + I^{-1}(S_n) \cdot J(S_n), \qquad S_0 = \{Initial\ condition\}$$

Results

Simulation Setup: Experimental area was 100m x 100m. Source intensity was represented by count rate measured 1 meter away.

Estimation Result:

- Correctly clustering non-source areas and source areas required sufficient number of measurements (e.g. m>800).
- Source parameters were estimated accurately, given correct clusters of non-source areas and source areas.
- While increasing the number of measurements, the estimation error of MLE decreased and converged to a lower bound.

Table 1: Estimation of source position (α, β) and intensity μ with correct clusters of non-source/source areas

Number of	Source1			Source2			Source3			Source4			Source5		
measurements	α/m	β/m	μ/cps	α/m	β/m	μ/cps	α/m	β/m	μ/cps	α/m	β/m	μ/cps	α/m	β/m	μ/cps
400	30.0	29.7	958.8	40.4	9.9	307.3	50.1	49.5	510.4	62.3	82.0	623.1	70.2	49.9	305.9
600	30.0	30.0	988.7	40.0	9.9	298.1	50.0	50.0	514.5	61.9	82.1	591.4	70.0	50.3	304.0
800	30.0	30.0	1007.5	39.8	10.1	295.8	50.2	50.0	484.0	62.0	82.0	602.7	70.0	50.0	303.2
1000	30.0	30.0	1011.4	40.0	10.3	298.9	50.0	50.0	497.1	62.0	82.0	602.9	70.0	50.0	301.4
2000	30.0	30.0	999.8	40.0	10.0	300.5	50.0	50.0	498.1	62.0	82.0	602.4	70.0	50.0	301.1
True Value	30.0	30.0	1000.0	40.0	10.0	300.0	50.0	50.0	500.0	62.0	82.0	600.0	70.0	50.0	300.0

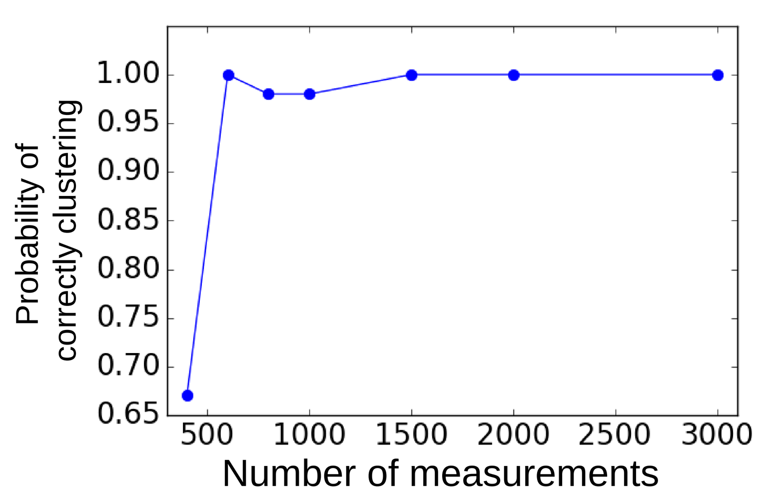

Figure 7: Clustering accuracy under different number of measurements

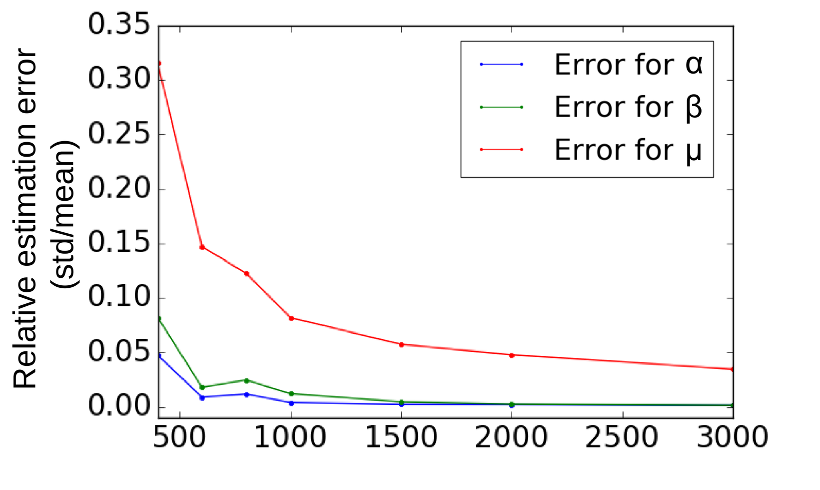

Figure 8: Estimation error under different number of measurements

Conclusions

The pre-filter framework identified source areas and located multiple sources accurately with sufficient measurements. It was also observed that increasing the number of measurements would not significantly improve the estimation when the number of measurements were already sufficient.

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Reference:

[1] T. Hastie, R. Tibshirani, and J. H. Friedman, "6. Kernel Smoothing Methods," in *The Elements of Statistical Learning*, 2nd ed., New York: Springer, 2009, pp.191-216.

[2] S. Beucher, and F. Meyer. "The morphological approach to segmentation: the watershed transformation." *OPTICAL ENGINEERING-NEW YORK-MARCEL DEKKER INCORPORATED-* 34 (1992): 433-433.

[3] A. Charnes, E. L. Frome, and P. L. Yu, "The equivalence of generalized least squares and maximum likelihood estimates in the exponential family", J. Amer. Statist. Assoc. Theory Meth. Section, vol. 71, no. 353, pp. 214-222, Mar. 1976.