Detection and Localization of Events in Imaging Sensor Nets

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***Abstract*— We consider an *Imaging Sensor Net,* in which a stationary collector node employs imaging techniques for localization and data collection from sensor nodes without geolocation or inter-networking capabilities. Sensors that are near enough to an event of interest become *active.* We consider a dense sensor field, in which multiple sensors are activated by the same event. The collector scans the sensor field with a directional antenna. Active sensors which fall in the beam electronically reflect the collector's beacon, thus creating a radar-like geometry. The collector processes the observations obtained in multiple beams to obtain maximum likelihood estimates of the locations of events of interest.**

I. Introduction

Sensor networks typically operate under stringent energy constraints, with communication being one of the most energy-intensive tasks that a sensor node must perform. Thus, the architecture usually proposed for sensor networks is multihop wireless ad hoc relay, in which individual sensor nodes need only expend enough energy to talk to their neighbors. Since a key component of the data collected from sensor networks is the location of events detected by the sensor nodes, an implicit assumption is that sensor nodes have estimates of their own locations (e.g., from GPS capability at the sensors, or a number of possible localization algorithms [1], [2], [3]), and include it in the data they send.

The work in this paper is based on an alternate paradigm, which we first introduced in a somewhat different form in [4], [5]. We use the general term *Imaging Sensor Nets* for the class of architectures we consider, in which sensor functionality and the amount of data sent by the sensors is reduced to a bare minimum, so that, even with severe energy constraints, the link budget is adequate for directly reaching a collector node. The sensors do not have geolocation or inter-networking capabilities. Rather, they can electronically reflect the collector's beacon (and possibly add low-rate data modulation to the beacon). The collector can then use radar and imaging techniques to localize the sensors that respond to it, and also to demodulate sensor data if any. Since localization of events is of fundamental interest, in this paper, we focus on this problem, and ignore additional data that the sensors might send.

[0]This work was supported by the National Science Foundation under grants CCF-0431205, ANI-0220118 and EIA-0080134, and by the Office of Naval Research under grant N00014-03-1-0090.

While we considered sparse sensor networks with moving collectors in [4], [5], in this paper, we consider a stationary collector estimating the location of events detected in a densely deployed sensor field. Sensors that are near enough to an event of interest become *active,* with multiple sensors activated by the same event. The collector scans the sensor field with a directional antenna. Active sensors which fall in the beam electronically reflect the collector's beacon, thus creating a radar-like geometry. The collector processes the observations obtained in multiple beams using maximum likelihood (ML) techniques to estimate the locations of events of interest.

This paper is organized in the following manner. In the first part of Section II, a system model for an imaging sensor net with a stationary collector is described. In Sections II-A and II-B, ML localization algorithms are developed. We first assume that an event actives a single sensor, and then consider multiple sensor activation. The performance of these algorithms is studied using simulations in Section III, along with discussion of some performance tradeoffs as a function of system parameters.

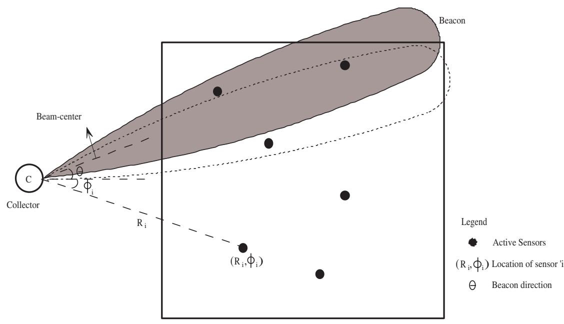

Fig. 1. An Imaging Sensor Net with a stationary collector and dense sensor nodes.

II. Imaging Sensor Net with Stationary Collector

The sensors are assumed to be deployed in a rectangular sensor field, and placed at equal intervals along both coordinate directions, however, this assumption can be easily relaxed to more general network topologies. In this paper, a sensor field with a stationary collector node is presented in contrast to the airborne moving collector approach proposed in [4], [5].

The underlying phenomenon being sensed is modeled as discrete events that occur at random locations on the field. Probabilistic or deterministic models determine how events activate sensors in their vicinity - precise activation models are presented in Sections II-A and II-B. The sensors convey one bit of information about the occurrence of an event using a 'yes-no' (or 'on-off') type of signaling. Sensors that detect an event in the vicinity are termed 'active' sensors. The active sensors signal a '1' by transmitting a signal $s(t)$ and, the sensor that are not active, signal a '0' by the absence of a signal. The system performance could potentially be improved by actively signaling for '0' as well. In general, the signaling strategy could be optimized as a function of the anticipated density of the active and inactive sensors, and could benefit from local inter-sensor coordination. However, no such optimization is attempted here.

The collector node sweeps the sensor field with a beacon, using an antenna that produces a narrow beam, that is either electronically or mechanically steered to illuminate different regions of the field in different "snapshots." One possible choice for the beacon is a direct sequence spread spectrum signal with a long enough period to avoid range ambiguity when it is reflected by the sensor nodes. In this case, the collector would have to estimate the round-trip delay, and hence the range of the sensor responding to the beacon, by correlating the return signal with the spreading code it sent out. In this paper, we focus on fundamental tradeoffs in localization, rather than on baseband signal processing at the collector. We therefore adopt, as in our prior work [4], [5], an idealized model in which the sensors respond by sending a signal in response to a trigger sequence in the beacon. That is, we adopt a one-shot model for the sensor response (the sensor sends back a short Barker spreading code if it is active), rather than a continuous reflection of the collector's beacon, thus simplifying the simulation of the baseband signal processing at the collector.

The reflection of the collector's beacon by the sensors creates a radar geometry. As the beacon sweeps the field, the angle of the beam is incremented by a small amount for successive snapshots, such that an active sensor is illuminated in a large number of snapshots. The scenario is therefore similar to Synthetic Aperture Radar (SAR). The collector uses SAR-like processing to image the sensor field. For sparse sensor fields, where an event activates only the sensor nearest to it, the techniques considered here are as in [4], [5], except that the geometry is somewhat different because of the radial sweep of the collector's beacon. For dense sensor fields, we need to extend these methods to localize events that activate multiple sensors.

A. Localization of a Single Active Sensor

In this initial development it is assumed that each event activates the closest sensor and the events are sparsely distributed in the sensor field. The latter assumption implies that there is no inter-sensor interference and hence, it is sufficient to solve the problem of localizing a single active sensor in the field. The estimation problem is formulated in polar coordinates with the collector node at the origin and the angular coordinate along the x-axis chosen to be '0'. Let the active sensor be located at (R, Φ), where R is the distance between the collector and the active sensor. The antenna at the collector node is assumed to be ideal with unity gain within the sector subtending an angle 2Θ at the collector and zero gain outside (Figure I). The antenna beamwidth function is

$$I(\theta) = \begin{cases} 1 & \text{if } |\theta| < \Theta \text{ and sensor is active} \\ 0 & \text{if } |\theta| > \Theta \end{cases} . \quad (1)$$

The path loss in the signal is also assumed to be compensated by appropriate gain at the collector in this antenna model. This ideal beamwidth function determines which sensors contribute to a snapshot depending on the location of the sensor and direction in which the beacon is pointing. In snapshot j, the center of the beacon makes an angle ϕ_j with the x-axis.

The active sensor transmits a complex baseband signal $s(t)$ in response to the trigger sequence in the beacon. The complex baseband received signal $r_j(t)$ at the collector node in the jth snapshot due to a sensor at (R, Φ) is

$$r_j(t) = s(t - \tau(R))I(\Phi - \phi_j)e^{j\theta_j} + n_j(t), \quad (2)$$

where θ_j is a random phase term, $\tau(R)$ is the round-trip delay from the collector node to the active sensor and $n_j(t)$ is the noise. Note that $r_j(t)$ may be a vector if there are multiple receive antennas at the collector.

The random phase term in (2) arises due to the lack of synchronization between the local oscillators(LO) at the sensor and the collector. However the frequency offset between the oscillators is assumed to be small enough that the relative phase is constant over the duration of the transmitted pulse. The random phases at each snapshot,$\{\theta_j\}$ are modeled as independent and identically distributed(i.i.d) over $[0, 2\pi]$.

Equation (2) can be rewritten in polar coordinates by making the transformation $t = \frac{2\rho}{c}$ and using the fact that $\tau(R) = \frac{2R}{c}$, where 'c' is the speed of light. Note also that the snapshots are equivalently indexed by the center of the beacon ϕ_j and allow a natural mapping of the snapshot index to the angular coordinate in the polar coordinate system.

$$r_j(\rho, \phi_j) = \tilde{s}(\rho - R)I(\Phi - \phi_j)e^{j\theta_j} + n(\rho, \phi_j) \quad j = 1, ..., J, \quad (3)$$

where $\tilde{s} = s(2\rho/c)$ and θ_j is the phase difference between the LOs at the sensor and collector in snapshot j. The received signal vector at the collector over all the snapshots is

$$\mathbf{r} = \mathbf{s} + \mathbf{n}\,, \quad (4)$$

and

$$s_j(R, \Phi) = \tilde{I}_j\ \tilde{s}(\rho - R)\ e^{j\theta_j},$$

where $\tilde{I}_j = I(\Phi - \phi_j)$ and $\mathbf{n}$ is an Additive White Gaussian Noise (AWGN) vector. Further, the number of times an active sensor is illuminated, N_{illum}, or the number of snapshots in which $\tilde{I}_j = 1$, is

$$N_{illum} = \frac{2\Theta}{\Delta\phi},$$

where $\Delta\phi = \phi_j - \phi_{j+1}$ or angle between successive snapshots.

The problem of obtaining location estimates for the sensor $(\hat{R}, \hat{\Phi})$ is modeled as a ML estimation problem in the presence of AWGN and the ML estimates are obtained by minimizing the euclidean distance between received and transmitted signals,

$$(\hat{R}, \hat{\Phi}) = \arg \max_{(R,\Phi),\{\theta_j\}} -\sum_{j=1}^{J} \|r_j - \tilde{I}_j \ \tilde{s}(\rho - R)e^{j\theta_j}\|^2.$$

The ML location estimates for the location is

$$(\hat{R}, \hat{\Phi}) = \arg \max_{(R,\Phi)} \sum_{j=1}^{J} \tilde{I}_j \ |\langle r_j, \tilde{s}(\rho - R)\rangle|. \quad (5)$$

Equation (5) provides the optimal ML procedure for estimating the location of the active sensor. The sufficient statistics are obtained by matched-filtering the received signal at every snapshot against the transmitted signal $\tilde{s}$ along the range, ρ, coordinate. The magnitudes of these sufficient statistics are then filtered in the azimuth, ϕ, coordinate with a filter matched to the antenna beamwidth function $\tilde{I}$. The magnitudes are used since the system is non-coherent due to the lack of synchronization between the sensors and the collector. The optimal processing is thus two-dimensional matched filtering that can be decomposed into two successive one-dimensional matched filtering operations along the range and azimuth directions.

B. Localization of an Event using Multiple Sensor responses

In the previous subsection, each event was detected by exactly one nearby sensor. In a dense sensor network this would certainly not be the case and it is also desirable from the point of view of robustness for multiple sensors to detect an event. In this subsection, a sensor activation model where each sensor detects all events within a radius, R_{det}, around it is used. This is equivalent to using a model where all sensors in a radius, R_{det}, around the event, detect the event. When the events are far enough apart, it is sufficient to study the detection and localization of a single event and all the active sensors corresponding to it.

Suppose that K sensors located at $\{(R_k, \Phi_k)\}$ are activated by the event. The received signal in snapshot j in polar coordinates is

$$r_j(\rho, \phi_j) = \sum_{k=1}^{K} \tilde{s}(\rho - R_k) \ \tilde{I}_{j,k} \ e^{j\theta_{j,k}} + n(\rho, \phi_j) \quad j = 1, ..., J, \quad (6)$$

where $I(\Phi_k - \phi_j) \triangleq \tilde{I}_{j,k}$.

In the ML estimation framework, the log-likelihood function to be be maximized is

$$L(\mathbf{r}|R_k, \Phi_k, \{\theta_{j,k}\}) = -\mathbf{r}^H\mathbf{r} + 2\,Re\{\mathbf{r}^H\mathbf{s}\} - \mathbf{s}^H\mathbf{s} \quad (7)$$

In (7), retaining only the parts that are dependent on the maximization variables,$\{(R_k, \Phi_k)\}$ and $\{\theta_{j,k}\}$, the second and third terms become

$$Re\{\mathbf{r}^H\mathbf{s}\} = \sum_{j=1}^{J}\sum_{k=1}^{K} \tilde{I}_{j,k}|A_j(R_k)|\cos(\theta_{j,k}),$$

$$\mathbf{s}^H\mathbf{s} = 2\sum_{j=1}^{J}\sum_{\substack{k,l=1\\ l>k}}^{K} \tilde{I}_{j,k}\tilde{I}_{j,l}|C(R_k - R_l)|\cos(\theta_{j,k} - \theta_{j,l}),$$

defining $C(R_k - R_l) = \langle \tilde{s}(\rho - R_k), \tilde{s}(\rho - R_l)\rangle$ and $A_j(R_k) = \langle r_j, \tilde{s}(\rho - R_k)\rangle$.

If $|A_j(R_k)| \gg |C(R_k - R_l)|, \forall j$, then the log-likelihood function after maximization over $\{\theta_{j,k}\}$ can be approximated (with details omitted here due to lack of space) as

$$\begin{aligned} L(\mathbf{r}|R_k, \Phi_k) \ = \ & 2\sum_{j=1}^{J}\sum_{k=1}^{K} \tilde{I}_{j,k}|A_j(R_k)| \\ & -2\sum_{j=1}^{J}\sum_{\substack{k,l=1\\ l>k}}^{K} \tilde{I}_{j,k}\tilde{I}_{j,l}|C(R_k - R_l)| \end{aligned} \quad (8)$$

The second term in (8) depends only on the relative locations of the K active sensors in the field, which is fixed once a certain activation model is assumed and it is independent of the absolute locations of the active sensors. Hence, this term can be dropped from the log-likelihood function since it is a constant for any location of the event.

Therefore, the simplified ML estimation rule is

$$(\hat{R}, \hat{\Phi}) = \arg \max_{(R,\Phi)} \sum_{j=1}^{J}\sum_{k=1}^{K} \tilde{I}_{j,k} \ |\langle r_j, \tilde{s}(\rho - R_k)\rangle|. \quad (9)$$

Equation (9) is very similar in form to (5) corresponding to the single active sensor case. The sufficient statistics are still obtained by matched filtering the received signal at every snapshot in the range coordinate with the transmitted signal,$\tilde{s}$. The optimal processing involves two-dimensional matched filtering that is again performed in two successive steps. First, the received signal is matched filtered against the transmitted signal. Second, the magnitude of the output of the first step, is matched filtered against a two-dimensional effective beamwidth function,$\tilde{I}_{j,k}$, in analogy to the single sensor activation model.

This effective beamwidth function can be constructed using the physical antenna beamwidth function and the activation model for the active sensors and is dependent only on those two factors. But, simplification of (8) was possible since the transmitted signal, $\tilde{s}$, was assumed to have a very sharp auto-correlation function. This can be realized practically by using a signal, s, with a sufficiently high bandwidth. Importantly, this approach is independent of the activation model at the sensors as long as it is deterministic and is known at the collector.

III. Simulation Results

The system described in Section II was simulated using the following parameters.The sensor field contains 40000 sensors (100x100) arranged in a equally spaced square grid with a side of length 500*m*. The collector node is 200*m* from an edge of the field and halfway along it, with a height of 25*m* as shown in Figure I. Events are chosen randomly in the field at a sufficient distance from the edges to avoid edge effects and the density is assumed to be high enough that every event occurs very close to a sensor so that it is sufficient to localize this sensor. Events activate the sensors using either of the two activation models described earlier. When illuminated, each active sensor transmits $s(t)$ which is an 11-chip Barker sequence using a BPSK constellation with square-root raised cosine pulse with excess bandwidth of 0.5. The antenna at the collector is ideal with a nominal beam angular spread of 12.17. The beacon sweeps an angle of 0.21 between successive snapshots so that the nominal number of times an active sensor is illuminated by the beacon, $N_{illum} = 12.17/0.21 = 59$. The RMS signal bandwidth, $\mathcal{W}_{rms}$, is approximately 13 *MHz*. The signal-to-noise ratio (SNR) at the receiver per snapshot, is the ratio of the received signal power to the total noise power added at the receiver per sensor transmission i.e. SNR $= \|s\|^2/(2\sigma^2)$ where the noise is i.i.d CN$(0, 2\sigma^2)$.

A. Scale-Invariant System Dimensions

The description of system dimensions and characterization of system performance in terms of scale-invariant quantities enables prediction of performance of another system with different physical dimensions but the same relative dimensions. To this end, we introduce one parameter each for the 'x' and 'y' directions, that are used as the normalizing quantity or so-called 'units' to achieve scale invariance. The 'x' and 'y' estimates are

$$\hat{x} = \hat{R}\cos\hat{\Phi} \quad \text{and} \quad \hat{y} = \hat{R}\sin\hat{\Phi} \tag{10}$$

where both estimates take the dimension of $\hat{R}$ and relation between the errors in 'x' and 'y' to the errors in 'R' and 'Φ' is

$$\begin{aligned} \Delta x &= \Delta R\cos(\Phi) - R\sin(\Phi)\Delta\Phi \\ \Delta y &= \Delta R\sin(\Phi) + R\cos(\Phi)\Delta\Phi \end{aligned} \tag{11}$$

The Cramer-Rao Lower Bound for estimating the range using delay estimation is

$$\sigma^2_{\hat{R}} = \frac{c^2}{16\pi^2 W^2_{rms}\ \text{SNR}\ N_{illum}} \tag{12}$$

This motivates the choice of the reciprocal of the root-mean-square(RMS) signal bandwidth, $\mathcal{W}_{rms}$, expressed as a distance, as the normalizing parameter along the 'x' and 'y' directions, $R_0 = c/\mathcal{W}_{rms}$, where c is the speed of light, and $\mathcal{W}_{rms}$ is a nominal signal bandwidth. $\sigma^2_{\hat{R}}$ has the dimension of R_0^2 and $\hat{\Phi}$ is dimensionless. The simulation results are presented with R_0 as the unit of distance and the system parameters presented in Section III can be easily scaled by R_0 to obtain a scale-invariant system.

B. Single Sensor Activation Model

The optimal ML detection rule in (5) was used to detect and estimate the location of a single active sensor corresponding to a randomly located event in the field. It was observed that at SNRs greater than 2*dB* all active sensors were detected. The locations of the active sensors were first estimated in polar coordinates and then transformed to cartesian coordinates. In Figures 2 and 3, RMS estimation error in the 'x'-coordinate and 'y'-coordinate of the active sensor is plotted against SNR for various values of N_{illum} which is linearly dependent on the beam angular spread, 2Θ, if the angle between snapshots $\Delta\phi$ is kept constant. As expected (from (12)) the estimation error decreases with increase in SNR. There is also a marginal improvement in performance with increase in N_{illum} as indicated by (12), since better noise averaging in the delay estimation is obtained with increase in the number of snapshots. These are however only qualitative results since variances of $\hat{x}$ and $\hat{y}$ are non-linear functions of the variances of $\hat{R}$ and $\hat{\Phi}$ as seen in (11). Equation (11) also shows that resolution at any given location (R, Φ) is a function of (R, Φ) and therefore, the results presented here represent RMS estimation errors averaged over all locations.

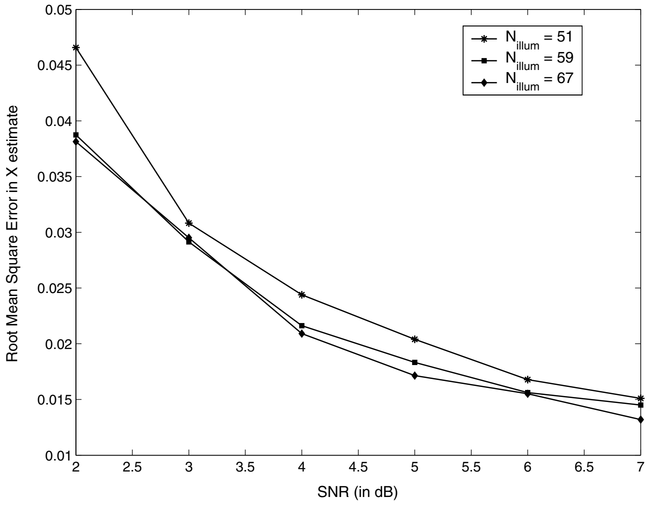

Fig. 2. Performance of Single sensor activation model: Root Mean Square Error in X coordinate of the event versus SNR for various values of N_{illum}

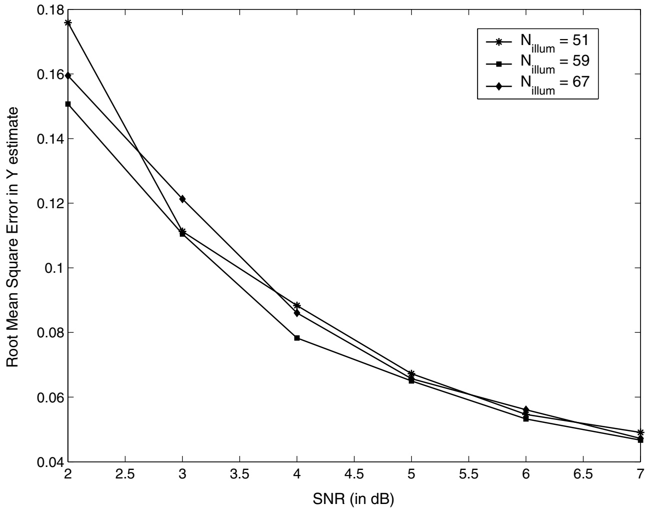

Fig. 3. Performance of Single sensor activation model: Root Mean Square Error in Y coordinate of the event versus SNR for various values of N_{illum}

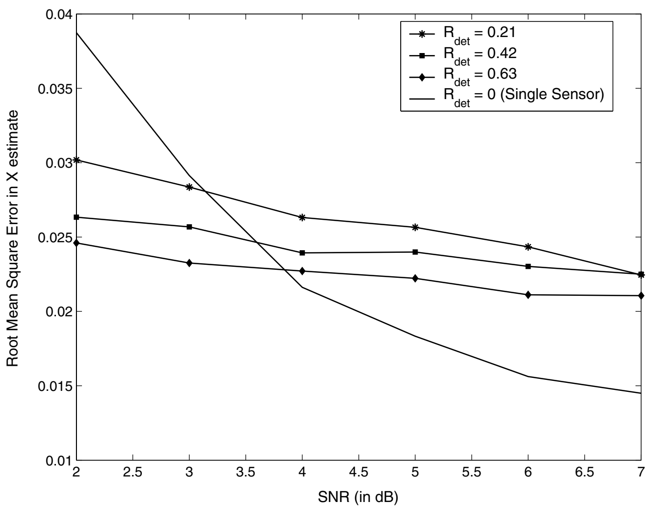

Fig. 4. Performance of Multiple sensor activation model: Root Mean Square Error in X coordinate of the event versus SNR for various sensor detection radii, R_{det}

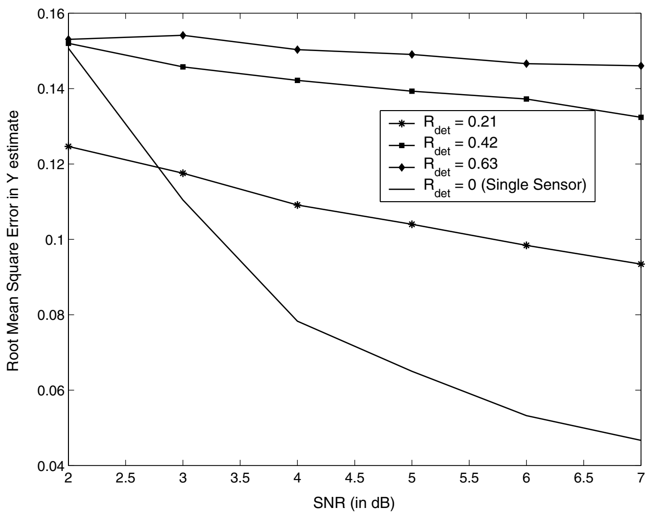

Fig. 5. Performance of Multiple sensor activation model: Root Mean Square Error in Y coordinate of the event versus SNR for various sensor detection radii, R_{det}

C. Multiple Sensor Activation Model

In figures 4 and 5, the RMS estimation error in the 'x'-coordinate and 'y'-coordinate of the event are plotted against SNR for different sensor activation radii, R_{det} with all other parameters at their nominal value. The estimation error decreases with increase in SNR as in the single sensor case. At SNRs of 2-3dB estimation of the 'x' coordinate is better for multiple sensor activation as compared to single sensor activation. Further, the RMS error in the 'x' coordinate improves with increase in R_{det} due to the increased total received energy from multiple sensors transmitting. In the 'y' direction, however, the single sensor activation performs comparably with multiple sensor activation at low SNR but outperforms it at higher SNR. In fact, contrary to the 'x' coordinate, the RMS error in the 'y' coordinate increases with R_{det}. From (11), the errors are dependent on $\sin(\Phi)\Delta\Phi$ for the 'x' coordinate and on $\cos(\Phi)\Delta\Phi$ for the 'y' coordinate. For the parameter values chosen here, most locations correspond to small Φ values leading to greater dependence of 'y' error variance on the error in $\hat{\Phi}$, which for increasing R_{det} gets progressively worse. Also, these large errors in $\hat{\Phi}$ do not affect the 'x' error variance as much due to a $\sin\Phi$ type dependence. Nevertheless, at low SNRs better and more robust performance can be obtained from the multiple sensor activation model.

IV. CONCLUSION

Imaging sensor nets with a stationary collector are shown to provide good event localization. The single sensor activation model (appropriate for a sparse sensor field) performs better when the SNR is large enough, but multiple sensor activation (as in a dense sensor field) provides more uniform and better performance at very low SNRs.

A large number of issues remain open. For the model at hand, a comprehensive investigation is needed for determining performance tradeoffs as a function of system parameters, and comparing the performance with estimation-theoretic bounds. Broader issues include data modulation and demodulation (in addition to localization), the use of multiple collectors to provide better resolution, coverage and diversity, and more detailed models tying events to sensor activation (e.g., the use of probabilistic models, especially to capture the effect of failed sensors) and sensor data.

REFERENCES

[1] N. Bulusu, J. Heidemann, D. Estrin, and T. Tran, "Self-configuring localization systems: Design and experimental evaluation," *ACM Trans. on Embedded Computing Systems*, vol. 3, no. 1, pp. 24–60, 2004.

[2] N. Priyantha, H. Balakrishnan, E. Demaine, and S. Teller, "Anchor-free distributed localization in sensor networks," MIT LCS, Tech. Rep. TR-892, Apr. 2003.

[3] A. Savvides, H. Park, and M. Srivastava, "The bits and flops of the n-hop multilateration primitive for node localization problems," in *Proc. First ACM International Workshop on Wireless Sensor Networks and Application*, Atlanta, GA, Sept.

[4] B. Ananthasubramaniam and U. Madhow, "Virtual radar imaging for sensor networks," in *Proceedings of the third international symposium on Information processing in sensor networks*. Berkeley, California, USA: ACM Press, New York, April 2004, pp. 294–300.

[5] ——, "Virtual radar approach to event localization in sensor networks," in *Proceedings of the International Symposium on Information Theory(ISIT 2004)*, Chicago, CA, June 2004, p. 517.