Virtual Radar Imaging for Sensor Networks

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ABSTRACT

Most approaches to sensor data collection in the literature are based on a multihop wireless relay between sensor nodes forming an ad hoc network to reach a remote data-processing destination. In this paper, we propose an alternative Virtual Radar paradigm, which, in its most rudimentary form, is implementable with sensor nodes without networking capabilities. We introduce this concept for a simple setting in which each sensor only has one bit of information to send (e.g., indicating whether the level of a certain chemical has crossed a threshold). "Active" sensors (those which have one to send) respond to a beacon sent by the collector node, precisely timed with a trigger sequence in the beacon. The collector node uses a modified version of synthetic aperture radar processing to obtain an "image" of the activity in the sensor network.

Categories and Subject Descriptors

E.4 [**Coding and Information Theory**]: Formal Models of communication; B.4 [**Input/Output and Data Communications**]: Data Communications Devices—*receivers*

General Terms

Design

Keywords

Sensors, Data collection, SAR, Location Estimation, Imaging

1. INTRODUCTION

Sensor networks consist of a large number of ubiquitously deployed (possibly randomly placed) sensor nodes with communication and computation capabilities. For many applications, sensor nodes are severely constrained in energy. This implies that one of the key bottlenecks in realizing sensor networks is the process of collecting data from them since transmission of data typically requires significantly more energy than sensing or computation. Most approaches to sensor data collection in the literature are based on multihop wireless relay between sensor nodes forming an ad hoc network, in order to reach a remote destination where the data is to be processed. This is a sensible approach in many situations in which the energy budget at the sensor node which originally obtains the data does not allow communication in a single hop with the destination. However, this approach is based on some important assumptions. First, it is assumed that the data being relayed is self-sufficient. Since the location of the phenomena being sensed is critical to many applications, the data being transmitted must include the location of the originating sensor node. However, the absolute locations of the sensors may not be known, and positioning technology such as GPS may or may not be available due to jamming (e.g., in hostile environments), or attenuation (e.g., indoors), or the cost of including a GPS receiver in the sensor. The second key assumption is that the sensor nodes are sophisticated enough to be able to set up an ad hoc network that routes to a desired destination, possibly using application-specific protocols [1, 2] rather than generic ad hoc network protocols [3]. Several prototyping efforts are underway for realizing these assumptions, by packing more and more functionality into smaller and smaller sensor nodes by innovations in hardware [4] and software [5]. Complementing these are theoretical research efforts which attempt to exploit correlation between observations at neighboring sensors, using information-theoretically motivated distributed source coding techniques, in order to reduce the amount of data to be sent [6, 7, 8].

In this paper, an alternative method for sensor network data collection is proposed that does not require the sensor nodes to know their locations, nor do they need to form an ad hoc network. In essence, the idea is to dumb down the functions to be performed by individual sensor nodes, so that it suffices to use very simple nodes that can be realized with classical hardware and digital logic. This is achieved by moving the complexity from the sensor nodes to a special *collector node*. The key idea is to employ a *virtual radar* paradigm for sensor data collection. One possible realization of this concept, pictured in Figure 1, might be as follows:
(a) The collector node (e.g., an aircraft or UAV, or a vehicle at the edge of the sensor field) collects multiple snapshots of activity in the sensor network. The data collection for each

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snapshot is initiated by the collector node sending a beacon to the sensor nodes;
(b) The sensor nodes that hear the beacon respond if they have some activity to report, timing their response precisely with respect to a "start transmission sequence" in the beacon. All sensor nodes may actually be identical, so that all nodes with activity to report may send the same waveform in response to the beacon;
(c) The collector node processes the net received signal received from the sensor nodes in a manner similar to synthetic aperture radar imaging, using the multiple snapshots, as well as possibly a receive antenna array, to resolve signals from different sensors. The waveform sent by the sensors should therefore have properties similar to that of a good radar waveform [9].
(d) The collector generates an "activity map" of the sensor field using radar signal processing techniques [9][10] [11]. It is assumed that the collector node knows its own location at the time of different snapshots (e.g., an aircraft may know its own GPS location, as well as its height relative to the sensor field). Thus, it can obtain the absolute locations of sensors with activity to report, up to the resolution of this virtual radar imaging technique.
(e) Actions based on the activity map are taken. This may be based directly on the map (e.g., dropping neutralizing agents on a chemical spill), or may involve more detailed data collection from the centers of activity.

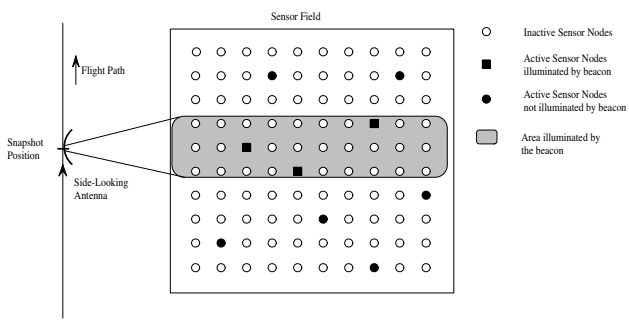

Figure 1: A collector node obtaining multiple snapshots based on responses of active sensor nodes to its beacon.

Section 2 contains a detailed discussion of the virtual radar concept in the context of a simplified example of sensors arranged on a rectangular grid. The initial part of this section discusses how the proposed system emulates synthetic aperture radar (SAR). The succeeding two parts provide a model of the system and description of the SAR reconstruction algorithm . Section 3 describes how algorithms that improve upon those in SAR can be employed by exploiting the specific features of the proposed system. These methods apply for a general placement of sensor nodes too. Section 4 presents a sample link budget analysis for our choice of system parameters followed by the simulation results that bring out the inadequacy of standard SAR techniques and illustrate the improvements provided by the modified methods. Section 5 presents concluding remarks on the techniques described in this paper.

2. EMULATING SYNTHETIC APERTURE RADAR

For simplicity, it is assumed that the sensors are deployed in a rectangular sensor field, and placed at equal intervals along both coordinate directions. The proposed methods apply for general network topologies as well. These sensors have some computational capability and also act as transmitters of the sensed data. The data is collected by a *collector node* and jointly processed to extract the required information. The collector node is not computationally constrained, and hence can perform complex operations to detect, estimate and process the transmitted data. The configuration in our example models an airborne collector node which flies parallel to one edge of the sensor field. However, similar ideas are applicable for different trajectories and for terrestrial collector nodes as well. While inter-sensor coordination can potentially be leveraged within the broad virtual radar framework, the schemes described in this paper do not require it.

The underlying phenomenon being sensed is assumed to be in the form of discrete events that occur at random locations in the field. Events activate sensors in the vicinity based on some probabilistic or deterministic model. The sensors thus convey information about the occurrence of the the event using a 'yes-no' type of signalling. These sensors that detect events are termed *active sensors*. The sensors transmit a '1' if they are active and '0' otherwise. The '1' is conveyed by the sensor by transmitting a signal $s(t)$ while '0' is conveyed 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 attempt at such optimization is made in this initial exposition.

The following algorithm is proposed to emulate a swath-mode SAR system[9]. The collector node illuminates a part of the field with a beacon using a side looking antenna as shown in Figure 1. The beacon carries a data sequence that triggers active sensors in that part of the field to transmit $s(t)$. Such a response to a common trigger sequence ensures that the sensors act as virtual reflectors, with the same round trip propagation delay as in SAR. This is critical since SAR relies primarily on this propagation delay to estimate the range of the object. The collector node takes multiple snapshots of the field from different locations along its path of motion.

2.1 System Model

Let the position of the collector node at snapshot j be $\mathbf{v}_j$(shown in Figure 1). The 3-dB beam width of the side-looking antenna is B and the antenna is assumed to be ideal with unity gain within the beam width and zero gain outside. This unity gain also implies that the path loss in the signal is ignored and is assumed to be compensated by appropriate gain at the collector node. Suppose there are K active sensors with positions $\underline{z} = \{\mathbf{z}_k, k = 1, ..., K\}$, where $\mathbf{z}_k$ may be a two- dimensional vector for sensors on a plane, or three-dimensional if the elevation of the sensors is to be estimated in addition to position on a plane. Further, the collector node is assumed to move along a straight line parallel to the 'y' axis of the coordinate system.

Each active sensor illuminated by the beacon sends the

same complex baseband signal $s(t)$. This signal is modulated on a sinusoidal carrier of frequency f_0 Hz. The transmitted passband signal is $\tilde{s}(t) = Re\{s(t)e^{j2\pi f_0 t}\}$. The complex baseband received signal $r_j(t)$ at the collector node at snapshot j is given by

$$r_j(t) = \sum_{k=1}^{K} A_{j,k} s(t - \tau_{j,k}) e^{-j2\pi f_0 \tau_{j,k}} + n_j(t), \quad j = 1, ..., J$$

where $A_{j,k}$ is a complex gain, $\tau_{j,k}$ is the round-trip delay from the collector node at position $\mathbf{v}_j$ to the active sensor at position $\mathbf{z}_k$, 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 local oscillators at the sensor and the collector are not synchronized, but 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 relative phases from snapshot to snapshot are modeled as independent and identically distributed over $[0, 2\pi]$. Assuming line of sight communication, the complex gains $A_{j,k}$ are given by

$$A_{j,k} = I_{j,k} e^{j\theta_{j,k}} \quad k = 1, ..., K, \quad j = 1, ..., J$$

where $I_{j,k}$ is a function that indicates if sensor k contributes to snapshot j, and $\theta_{j,k}$ are i.i.d., uniform over $[0, 2\pi]$. The indicator function $I_{j,k} = 1$ when sensor k is active and is also illuminated by the beacon in snapshot j and $I_{j,k} = 0$ otherwise. Other channel characteristics such as fading can be easily incorporated into the model for $A_{j,k}$, but we do not consider these in this paper.

The delay $\tau_{j,k} = \frac{2R_{j,k}}{c}$, where $R_{j,k}$ is the distance between the collector node and sensor k in snapshot j, and c is the speed of light. This is identical to conventional radar: the start transmission field reaches active sensor node k at a time $\frac{R_{j,k}}{c}$ after it is generated by the collector node, and the response of sensor k to it reaches the collector node at at a time $\frac{R_{jk}}{c}$ after it is generated by active sensor k. Since the geometry is exactly the same as in SAR, SAR techniques can be used to recover the locations of the active sensors. The SAR image reconstruction algorithm is developed and described in the following section.

2.2 SAR reconstruction algorithm

The real passband signal received at the collector node at snapshot j is of the form

$$\tilde{r_j}(t) = \sum_{k=1}^{K} \tilde{s}_j(t, \tau_{j,k}, A_{j,k}) + \tilde{n}_j(t), \quad j = 1, ..., J$$

where $\tilde{s}_j$ and $\tilde{n}_j$ are the real passband signal and noise components respectively. Quadrature demodulation of this signal gives the complex baseband received signal

$$r_j(t) = \sum_{k=1}^{K} A_{j,k} s(t - \tau_{j,k}) e^{-j2\pi f_0 \tau_{j,k}} + n_j(t), \quad j = 1, ..., J$$

But,

$$\tau_{j,k} = \frac{2R_{j,k}}{c} = \frac{2\|\mathbf{v}_j - \mathbf{z}_k\|}{c}$$

Choosing the coordinate system such that the collector node moves along the y-axis i.e., $\mathbf{v}_j = (0, v_j)$, and $\mathbf{z}_k = (x_k, y_k)$, the above expression can be rewritten as,

$$\tau_{j,k} = \frac{2\sqrt{x_k^2 + (y_k - v_j)^2}}{c}$$

The complex gain

$$A_{j,k} = e^{j\theta_{j,k}} I(v_j - y_k)$$

where $I(v_j - y_k) = \begin{cases} 1 & \text{if } |v_j - y_k| < B/2 \\ 0 & \text{if } |v_j - y_k| > B/2 \end{cases}$. This indicator function $I(v_j - y_k)$ is exactly the same as $I_{j,k}$ in the previous subsection, and indicates whether the sensor k is illuminated by snapshot j. Since the antenna is assumed to be ideal, the indicator function takes a value '1' for all active sensors illuminated by the beacon. If the antenna were non-ideal, the value taken by the indicator function would be determined by the sensor location and the antenna gain pattern. As in standard SAR, it is assumed that $x_k \gg B$ (the distance of each sensor from the path of the collector node is much larger than the half-beam width of the collector node's antenna). When $I(v_j - y_k) = 1$, we can employ the following approximation for the range and propagation delay from sensor k to the collector node in snapshot j:

$$R_{j,k} = x_k + \frac{(y_k - v_j)^2}{2x_k}$$

$$\tau_{j,k} \approx \frac{2x_k}{c} \tag{1}$$

The received signal for snapshot j can now be written as

$$r_j(t) = \sum_{k=1}^{K} A_{j,k} s(t - \frac{2x_k}{c}) e^{-j2k_0 x_k} + n_j(t), \; j = 1, ..., J$$

where $k_0 = 2\pi f_0/c$. This received signal is converted to a function of the spatial coordinates $(x, y = v_k)$ by setting $t = \frac{2x}{c}$,

$$r(x, y) = \sum_{k=1}^{K} I(y - y_k) s(\frac{2(x - x_k)}{c}) e^{j(\theta_{j,k} - 2k_0 x_k)} + n(x, y)$$

Since $e^{j\theta_{j,k}}$ is a uniform random phase factor, all deterministic phases can be absorbed into it. This yields

$$r(x, y) = \sum_{k=1}^{K} I(y - y_k) s(\frac{2(x - x_k)}{c}) e^{j\theta_{j,k}} + n(x, y)$$

The underlying field that is to be detected is of the form

$$\rho(x, y) = \sum_{k=1}^{K} \delta(x - x_k, y - y_k).$$

The received waveform can be written as

$$r(x, y) = \rho(x, y) * h(x, y)$$

where

$$h(x, y) = I(y) s(\frac{2x}{c})$$

The basic problem of recovering $\rho(x, y)$ is one of deconvolution or inversion of the filter $h(x, y)$. The simplest approach is to perform two dimensional matched filtering with respect to the filter $h(x, y)$ i.e. to convolve with $r(x, y)$ the filter $h^*(-x, -y)$. We do not care about the random phase

term $e^{j\theta_{j,k}}$ since we are interested only in the magnitude of $\rho(x,y)$.

Equation 1 is a standard approximation employed in SAR that the range of a sensor from the collector node is equal to the x-coordinate of the sensor. In other words, sensors at the same range in a given snapshot lie approximately on a line parallel to the y-axis. Therefore, the correlation along the x direction is commonly termed *range correlation*, and correlation along the y direction is termed *azimuth correlation*.

The first step in the deconvolution is the range correlation of the received signal with a signal matched to the transmitted signal, $s(\frac{2x}{c})$. The output of this processing is,

$$g(x,y) = \sum_{k=1}^{K} I(y-y_k) R_s(\frac{2x_k}{c}) e^{j\theta_{j,k}} + n_1(x,y)$$

where $R_s(.)$ is the autocorrelation function of the signal $s(t)$ and $n_1(x,y)$ is the noise colored by the matched filter. The next step is the correlation of $g_1(x,y)$ with a filter matched to $I(y)$, which is nothing but the antenna gain along the y-direction. This gives the estimate $\hat{\rho}(x,y)$ of the field $\rho(x,y)$,

$$\hat{\rho}(x,y) = \sum_{k=1}^{K} R_I(y_k) R_s(\frac{2x_k}{c}) e^{j\theta_{j,k}} + n_2(x,y)$$

where $R_I(.)$ is the autocorrelation function of $I(y)$ and $n_2(x,y)$ is the colored noise after both correlations. The final image is the magnitude of the function $\hat{\rho}(x,y)$.

Clearly, the resolution in the x-direction is determined by the function $R_s(\frac{2x}{c})$ and the resolution in the y-direction by $R_I(.)$. The choice of the signal $s(t)$ determines the range resolution while the azimuth resolution is determined by the antenna gain (and beamwidth) of the side-looking antenna.

3. IMPROVED MAXIMUM LIKELIHOOD PROCESSING

Standard SAR processing implicitly assumes phase coherence between the signal transmitted by the collector, and the reflected signal that it receives back. In this case, changes in phase between these two signals carry useful information about the field being imaged. However, in our virtual radar system, the oscillators at the sensor and the collector are not phase-coherent. Thus, reception can be improved by using noncoherent reception techniques that account for the lack of phase coherence. A method for Maximum Likelihood (ML) reception that achieves this is described below. As before, the received signal at each snapshot is modeled as

$$r_j(t) = \sum_{k=1}^{K} I_{j,k} s(t-\tau_{j,k}) e^{j\theta_{j,k}} + n_j(t),\ j = 1, ..., J$$

$$\mathbf{r} = \begin{pmatrix} r_1(t) \\ \vdots \\ r_J(t) \end{pmatrix}$$

where $\theta_{j,k}$ are iid uniform random variables, K is the total number of active sensors, $I_{j,k}$ is the function that indicates if active sensor k is illuminated in snapshot j and $\tau_{j,k}$ is the propagation delay between the sensor k and the collector node at snapshot j. The received vector

$$\mathbf{r} = \mathbf{s} + \mathbf{n}$$

where

$$s_j = \sum_{k=1}^{K} I_{j,k} s(t-\tau_{j,k}) e^{j\theta_{j,k}}$$

and $\mathbf{n}$ is a Additive White Gaussian Noise(AWGN) vector.

Assuming that the responses due to active sensors do not overlap, we can infer the locations of the active sensors one by one. Hence, we first develop an algorithm for detecting one active sensor.

We replace $I_{j,k}$ by I_j and $\theta_{j,k}$ by θ_j to simplify notation for the single sensor problem. The objective is to estimate the location X of the active sensor. This is a parameter estimation problem in the presence of AWGN. The likelihood function to be maximized in this problem is

$$L(\mathbf{r}|K) = e^{\frac{-\|\mathbf{r}-\mathbf{r}(\mathbf{X})\|^2}{2\sigma^2}}$$

where $\mathbf{s}(\mathbf{X})$ is the response of a single active sensor at position X in the absence of noise.

$$\mathbf{s}(\mathbf{X}) = \begin{pmatrix} \tilde{I}_1 s(t-T_1) e^{j\theta_1} \\ \tilde{I}_2 s(t-T_2) e^{j\theta_2} \\ \vdots \\ \tilde{I}_J s(t-T_J) e^{j\theta_J} \end{pmatrix}$$

where T_j are the propagation delays to each of the collector node positions. Note that $I_j = I_j(X)$, $j = 1, ..., J$, is a function of X.

We derive next the optimal estimator using two different approaches, paralleling classical derivations of noncoherent detectors. In the non-Bayesian approach, the phases $\{\theta_j\}$ are modeled as unknown, nonrandom parameters, while in the Bayesian approach, the phases are modeled as random, i.i.d., uniform over $[0, 2\pi]$.

Non-Bayesian Approach: The log-likelihood function is maximized jointly over X and θ_j. Maximizing the likelihood function is equivalent to maximizing the log likelihood function, and also identical to minimizing the Euclidean distance. The optimization reduces to

$$\hat{X}_{ML}(y) = \arg\max_X L(\mathbf{r}|X) = \arg\min_X \|\mathbf{r} - \mathbf{s}(\mathbf{X})\|^2$$

$$\hat{X}_{ML}(y) = \arg\min_X \sum_{j=1}^{J} \|r_j - \tilde{I}_j\ s(t-T_j) e^{j\theta_j}\|^2$$

To minimize the above function, θ_j are replaced by their maximum likelihood estimates. Hence,

$$\hat{X} = \arg\max_X \sum_{j=1}^{J} 2\tilde{I}_j\ |\langle r_j, s(t-T_j)\rangle| - \tilde{I}_j\ \langle s(t-T_j), s(t-T_j)\rangle$$

The second term in the cost function to be maximized is the autocorrelation function of the pulse, evaluated at $\tau = 0$. Hence, the second term is independent of the position of the sensor and can be dropped (if edge effects are negligible). The simplified function is

$$\hat{X} = \arg\max_X \sum_{j=1}^{J} \tilde{I}_j\ |\langle r_j, s(t-T_j)\rangle|$$

So, the sufficient statistic is $\sum_{j=1}^{J} \tilde{I}_j\ |\langle r_j, s(t-T_j)\rangle|$.

Although matched filtering against the pulse $s(t)$ is still the optimal, filtering in the y-coordinate is not the same as

that in SAR. The basic difference is that, due to the unknown phases $\{\theta_j\}$, the optimal processing is *noncoherent,* using only the magnitudes of the samples of the matched filter output. The succeeding filtering is the same as in SAR using a filter matched to $\tilde{I}$, which happens to be $\tilde{I}$ itself.

Bayesian Approach: Assuming that the random phases are uniformly distributed in the interval $[0, 2\pi]$, the θ_j are averaged out from the likelihood function. To shorten the expressions, define $\overline{s}(T_j) = s(t-T_j)$. The likelihood function then is

$$L(\mathbf{r}|X, \theta_j, j = 1, ..., J) = exp\left(-\frac{\sum_{j=1}^{J} \|r_j - \tilde{I}_j\ \overline{s}(T_j)e^{j\theta_j}\|^2}{2\sigma^2}\right)$$

$$L(\mathbf{r}|X,\theta_j) = exp\left(-\frac{\sum_{j=1}^{J} 2\tilde{I}_j|\langle r_j, \overline{s}(T_j)\rangle|cos\theta_j - \tilde{I}_j\langle\overline{s}(T_j), \overline{s}(T_j)\rangle}{2\sigma^2}\right)$$

Averaging out the θ_j we get,

$$L(\mathbf{r}|X) = \prod_{j=1}^{J} I_0\left(\frac{\tilde{I}_j\ |\langle r_j, \overline{s}(T_j)\rangle|}{\sigma^2}\right) exp\left(-\frac{\tilde{I}_j\ \langle\overline{s}(T_j), \overline{s}(T_j)\rangle}{2\sigma^2}\right)$$

where $I_0(.)$ is the Bessel Function of the first kind of order 0. Simplifying,

$$L(\mathbf{r}|X) = exp\left(-\frac{\sum_{j=1}^{J} \tilde{I}_j\langle\overline{s}(T_j), \overline{s}(T_j)\rangle}{2\sigma^2}\right)\prod_{j=1}^{J} I_0\left(\frac{\tilde{I}_j|\langle r_j, \overline{s}(T_j)\rangle|}{\sigma^2}\right)$$

As before, the term outside the product over j is independent of the location X if edge effects are neglected . Dropping this term and taking the logarithm, we get

$$\hat{X} = \arg\max_X \sum_{j=1}^{J} log\left(I_0\left(\frac{\tilde{I}_j\ |\langle r_j, \overline{s}(T_j)\rangle|}{\sigma^2}\right)\right) \qquad (2)$$

At high SNR, the approximation $I_0(x) \sim exp(a|x|)$ (which holds for x large) can be used to simplify the ML estimate as follows:

$$\hat{X} = \arg\max_X \sum_{j=1}^{J} \tilde{I}_j\ |\langle r_j, \overline{s}(T_j)\rangle| \qquad (3)$$

This coincides with the estimate derived using the non-Bayesian approach.

However, for low SNR, the Bayesian approach yields a different estimate from the non-Bayesian approach. For small x, the approximation $I_0(x) = 1 + x^2$ can be used to obtain the following low SNR estimate:

$$\hat{X} = \arg\max_X \sum_{j=1}^{J} log\left(1 + \frac{2\tilde{I}_j\ |\langle r_j, \overline{s}(T_j))\rangle|^2}{\sigma^2}\right) \qquad (4)$$

In all cases, the sufficient statistics are the magnitudes of the matched filter outputs $|\langle r_j, \overline{s}(T_j))\rangle|, \quad j = 1, .., J$, which are different from conventional SAR processing.

For multiple active sensors, instead of considering the location that maximizes the functions in (2), (3) or (4), one would simply pick the K locations giving the largest values. The number K of active sensors could either be known a priori, or could be estimated from the functions being maximized.

4. SIMULATIONS RESULTS

4.1 Simulation Parameters

In our simulations, the sensor field contains 10000 sensors arranged in an equally spaced square grid. The collector node is an aircraft that flies parallel to one side of the square grid at a certain distance away from the field. The active sensors are chosen randomly as a small fraction of the total sensors. The field is square of area 1 square kilometers. The aircraft flies at a height of 1000 meters, parallel to one side of the field at a distance of 2 kilometers. The carrier frequency is 100 MHz and the chip time of the Barker sequence is approx. 75 ns (i.e. bandwidth is approx. 13MHz) . The SNR at the receiver is defined on a per sensor per snapshot basis. The beam width of the side-looking antenna is 150 m. The active sensors respond to a beacon from the collector node by transmitting a length 11 Barker sequence. Each active sensor is illuminated by the beacon 60 times with distance between snapshots of 2.5m. There are totally 400 snapshots taken and each snapshot consists of 1000 range samples.

4.2 Sample Energy Budget

We present a sample link budget calculation for the preceding system. The peak transmit power at each active sensor is $1\mu W$. The antenna gains at the sensor and at the collector node are 2dB and 45dB respectively. The wavelength of the carrier in this system is 3m. Then, the ratio of receive power at the collector and the transmit power P_r/P_t at the maximum range is -25dB. Hence, the receive power at the collector is approx. 3.6 nW. At room temperature, the noise power in a bandwidth of 15Mhz is -102 dBm. For a receive amplifier with noise figure 10dB, the ratio of the SNR at the output to the input of the receiver is around 37dB. In our system, the design SNR at the output of the receiver is roughly 3dB, and this budget shows that we can work at lower peak powers and still maintain reasonably good performance. The energy consumption per active sensor at this peak power for one flyby is 48pJ.

4.3 Numerical Results

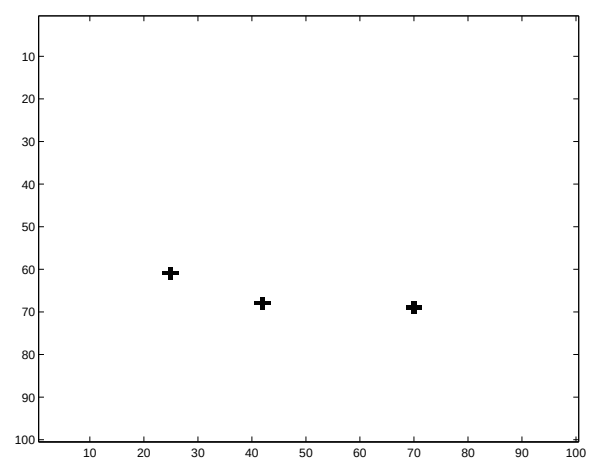

Figure 2: Position of the active sensors in the sensor field

Figure 2 shows the position of the active sensors in the

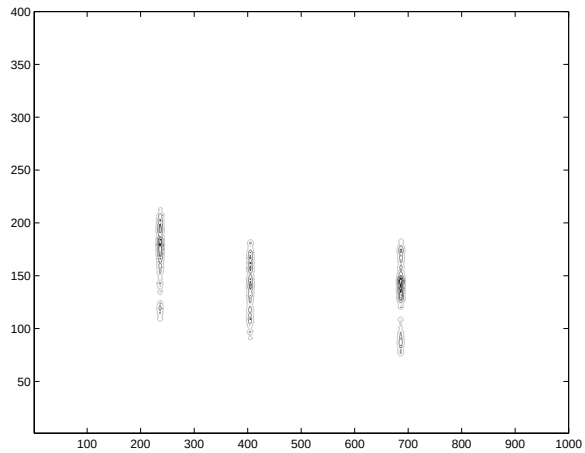

Figure 3: Reconstructed grayscale contour image of sensor field using standard SAR techniques with no noise

sensor field for this particular simulation run. Figure 3 is the reconstructed image of the sensor field using standard SAR techniques in the absence of noise. It is noticed that although there is no noise the estimate of the sensor locations is poor. This is attributed to the random phase terms in the received signal due to lack of carrier synchronization between transmitter and receiver, that does not occur in standard SAR. When the modified SAR techniques are used the performance significantly improves (Figure 4). This improvement is more pronounced in the case when the reconstruction is performed at an SNR of 4 dB (i.e. in the presence of significant noise). The simulations for this case are shown in Figure 5 and 6. In the latter two figures, a threshold was employed to convert the reconstruction into a binary image(In these figures, the threshold was chosen to be 60% of the peak magnitude). Whenever the magnitude of the reconstructed image exceeded the threshold it was set to '1' and to '0' otherwise.

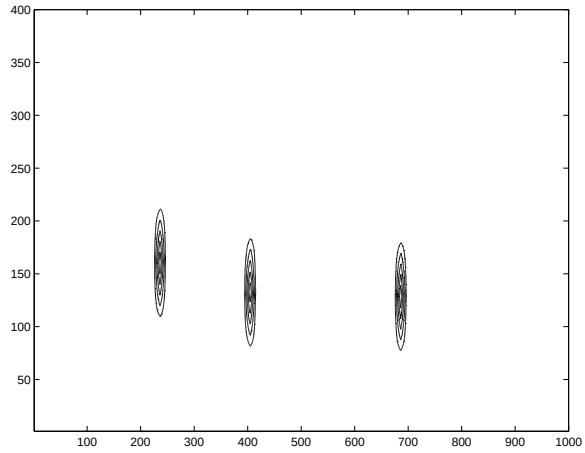

Figure 4: Reconstructed grayscale contour image of sensor field using modified SAR techniques with no noise

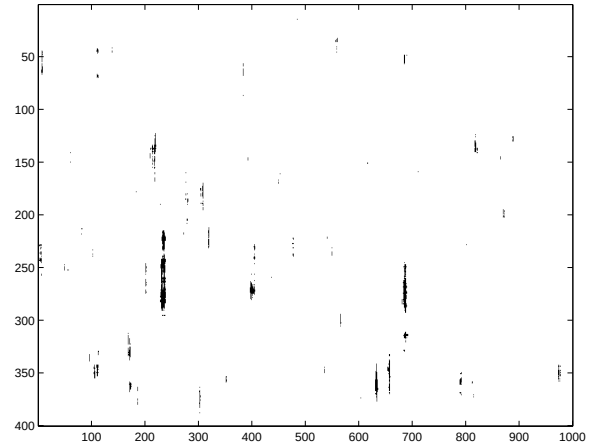

Figure 5: Reconstructed two-level image of sensor field using standard SAR techniques with noise and threshold, SNR = 4 dB

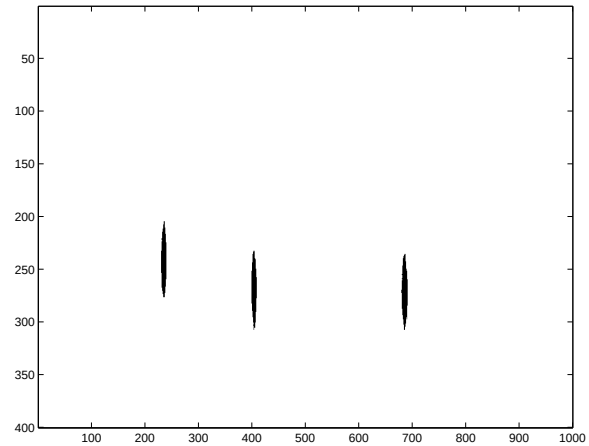

Figure 6: Reconstructed two-level image of sensor field using modified SAR techniques with noise and threshold, SNR = 4 dB

5. CONCLUSION

The results in this paper indicate the promise of the virtual radar approach to data collection in sensor networks. Large performance gains are obtained through modification of standard SAR processing to account for the random phases that arise because of lack of carrier synchronism between the sensors and the collector. The result of the processing is an image of the activity level in the sensor network.

Current research focuses on understanding how the proposed methods scale with the density of sensor nodes and of events triggering sensor activity, and how well they perform relative to fundamental estimation-theoretic bounds. In addition, there are many broader issues for future research, including diversity techniques for increasing energy efficiency, transmission of more complex data, improved signaling techniques (possibly with some local coordination between sensor nodes), exploitation of antenna arrays at the collector node, and integration with complementary concepts in source coding.

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