An Energy Efficient Iterative Method for Source Localization in Wireless Sensor Networks

Engin Masazade ♮†, Ruixin Niu †, Pramod K. Varshney †, Mehmet Keskinoz ♮
enginm@su.sabanciuniv.edu, rniu@ecs.syr.edu, varshney@syr.edu, keskinoz@sabanciuniv.edu
♮ Faculty of Engineering and Natural Sciences, Sabanci University, Istanbul 34956 TURKEY
†Electrical Engineering and Computer Science Department, Syracuse University, Syracuse, NY 13244 USA

***Abstract*—In this paper, we study the source localization problem in wireless sensor networks. Sensors transmit their quantized signal amplitude measurements to the fusion center and source location is estimated based on these quantized measurements. In this paper, we propose an energy efficient iterative localization scheme, where the algorithm starts with a coarse location estimate obtained from a set of anchor sensors. At each consecutive iteration, some of the non anchor sensors are activated which minimize an approximate Posterior Cramer Rao Lower Bound (A-PCRLB). Then, using the available information received at previous iterations as side information, the quantized data of each activated sensor is further compressed to conserve energy using distributed data compression techniques prior to transmission to the fusion center. Simulation results show that the proposed iterative method achieves the same estimation performance as when all the sensors transmit their quantized data to the fusion center within a few iterations, while at the same time significantly reducing the communication requirements resulting in energy savings.**

I. Introduction

Typically wireless sensor networks (WSN) are composed of a large number of densely deployed sensor nodes that co-operatively monitor the physical or environmental conditions of a scene of interest such as temperature or velocity of an object. Today WSNs are used in a wide range of application areas such as battlefield security, surveillance, environment or health monitoring, and disaster relief operations. In this paper, we study the source localization problem where the aim is to estimate the coordinates of a source emitting energy (e.g. acoustic source).

In a region of interest (ROI), an accurate estimation of the source location is possible by using the energy readings of individual sensors [1], [2]. In [1], a maximum likelihood (ML) approach is proposed by using analog sensor measurements. Since sensor nodes have limited resources (energy, bandwidth), it is imperative to limit the communication inside the network. Therefore, rather than transmitting the analog measurements, it is much preferable to quantize the sensor measurements to multi-bit data prior to transmission. For this reason, the ML approach for acoustic source localization has been extended for multi-bit quantized data in [2]. In this paper, we extend the method proposed in [2] by making it more energy efficient. First, we employ a small number of anchor nodes to obtain a coarse location estimate. Then, a few sensors at a time are activated to refine the location estimate in an iterative manner. Distributed compression is also employed at the non anchor sensors to further reduce the energy consumption.

In our method, we approximate the probability distribution function (pdf) of the source location which is assumed to be an unknown random variable at the fusion center. We first define this approximate pdf after gathering M-bit data from a small set of sensors which we call them as anchor sensors. The rest of the sensors have measurements from the source but they initially do not transmit their quantized measurements to the fusion center. Then, we use the idea of sensor selection similar to that presented in [3] and [4]. At each consecutive iterations, our algorithm selects a number of non-anchor sensors which minimize the PCRLB. Since we only know the pdf approximately, we rename this PCRLB as approximate PCRLB (A-PCRLB). We compare the performance of our algorithm with the approximate Cramer-Rao Lower Bound (A-CRLB) of the one shot location estimator where we substitute the ML estimate of source location with the actual source location. The one shot estimator requests multi-bit data from all the sensors in the field.

When sensors are densely deployed in a region of interest (ROI), the sensor measurements are likely to be spatially correlated and this correlation can be utilized to compress the quantized measurements of each sensor [5], [6], [7] to reduce energy consumption. In this paper, we employ data compression at each activated sensor prior to transmission. Given the multi-bit data received at previous iterations and the approximate pdf of location estimates, the fusion center calculates the conditional entropy of those sensors which are to be activated during an iteration. Then, the fusion center requests the measurement in a certain number of bits which is a function of the its conditional entropy. In here, the fusion center also recovers the compressed multi-bit data of activated sensors by using the previously received multi-bit sensor data as side information.

In this paper, we propose an iterative algorithm where at each iteration, using the present and past measurements we update the A-PCRLB of the location estimate and the approximate pdf of the estimated parameters. We keep activating the non-anchor sensors iteratively until the A-PCRLB converges to the A-CRLB of the one shot location estimate. In this scheme, the fusion center is assumed to know the sensors locations which is a reasonable assumption as the current technology allows the determination of locations, e.g., [8]. A local sensor does not need to know the joint distributions of the source location estimates or other sensor measurements which are all calculated at the fusion center. Simulation results show that A-PCRLB at consecutive iterations finally converges to the actual A-CRLB of the one-shot ML location estimate. Since we do not need the measurements of the sensors that are far away from the actual source location, the proposed iterative algorithm provides large communication savings while introducing some latency.

The rest of the paper is organized as follows. In Section II, we introduce the system model and review the ML location estimation method presented in [2]. In Section III, we present our iterative source localization method and in Section IV we give some numerical examples. Finally, Section V is devoted to our conclusions.

II. System Model

Figure 1 depicts an example wireless sensor network consisting of N sensors, $\{s_i, i = 1, 2, .., N\}$ that uses a parallel architecture where quantized measurement of each sensor can be directly delivered to the fusion center. Suppose that a signal (i.e. acoustic signal) is radiated from a position (x, y) that follows an isotropic power attenuation model which is provided later. The source energy measured at a reference distance d_0 is P_0. Fusion center is assumed to know the location of each sensor (s_i) given by (x_i, y_i). Distance between (s_i) and the source location is $d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}$. The received energy from the source denoted as a_i^2 at s_i is,

$$a_i^2 = \begin{cases} \frac{P_0}{d_i^n} & d_i > d_0 \\ P_0 & d_i \leqslant d_0 \end{cases} \tag{1}$$

where a_i is the received signal amplitude at s_i and n is the signal decay exponent. In this paper, we assume that the reference distance $d_0 = 1m$.

At each sensor, the received signal a_i is corrupted by an additive Gaussian Noise

$$r_i = a_i + w_i \tag{2}$$

where r_i is the noisy signal measurement at s_i. Here we assume that noise is independent and identically distributed across sensors with Gaussian distribution with parameters $\mathcal{N}(0, \sigma^2)$. At each sensor, r_i is then quantized into M bits.

A. Location Estimation with Quantized Data

We assume that each sensor sends its multibit (M-bit) data to the fusion center over an error free channel. D_i is the M-bit quantized data of s_i which can take any discrete value from 0 to $2^M - 1$. We define the number of quantization intervals as $L = 2^M$. We assume that the set of quantization thresholds for the i^{th} sensor is $\vec{\eta_i} = [\eta_{i0}, \eta_{i1}, \ldots, \eta_{iL}]$ where $\eta_{i0} = -\infty$ and $\eta_{iL} = \infty$. The quantization procedure for the i^{th} sensor is such that,

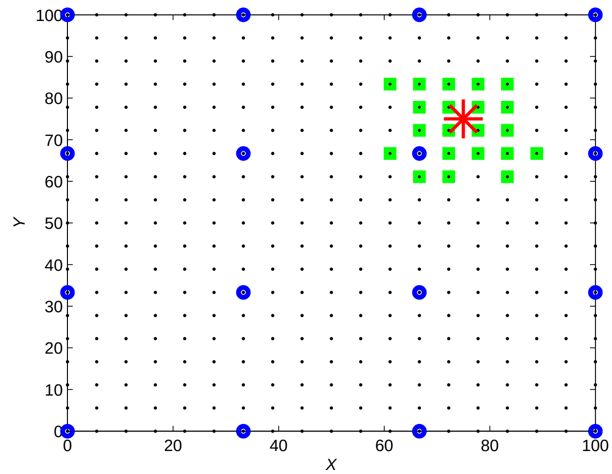

Fig. 1. Wireless Sensor Network Model (Black Points: Sensor Locations, Blue Circles:Anchor Sensors used for initial iteration, Green Squares: Activated Sensors after 7 iterations (p = 3 sensors are activated / iteration), Red Star:Source)

$$D_i = \begin{cases} 0 & -\infty < r_i < \eta_{i1} \\ 1 & \eta_{i1} < r_i < \eta_{i2} \\ \vdots & \\ L-2 & \eta_{i,(L-2)} < r_i < \eta_{i,(L-1)} \\ L-1 & \eta_{i,(L-1)} < r_i < \infty \end{cases} \tag{3}$$

Given source location (x, y), and Gaussian noise assumption, the probability that D_i takes a specific value l is

$$p(D_i = l|x, y) = p_{i,l}(\vec{\eta_i}, x, y) = Q\left(\frac{\eta_{il} - a_i}{\sigma}\right) - Q\left(\frac{\eta_{i,(l+1)} - a_i}{\sigma}\right) \tag{4}$$

where $Q(.)$ is the complementary distribution function of the standard Gaussian distribution.

$$Q(t) = \int_t^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{5}$$

After collecting data D from all the sensors in the network, the likelihood function at the fusion center has the form,

$$p(D|x, y) = \prod_{i=1}^{N} \prod_{l=0}^{L-1} p_{i,l}(\vec{\eta_i}, x, y)^{\delta(D_i - l)} \tag{6}$$

where $\delta(l)$ is the Kronecker delta function and is defined as,

$$\delta(t) = \begin{cases} 1 & t = 0 \\ 0 & t \neq 0 \end{cases} \tag{7}$$

The log-likelihood function of received data D is then,

$$\ln p(D|x, y) = \sum_{i=1}^{N} \sum_{l=0}^{L-1} \delta(D_i - l) \ln[p_{i,l}(\vec{\eta_i}, x, y)] \tag{8}$$

Let $\theta = [x, y]^T$ be the parameter vector to be estimated where T is the transpose operation. Maximum likelihood estimation

(MLE) $\hat{\theta}^{MLE}$ can be written as the following optimization problem:

$$\hat{\theta}^{MLE} = \arg\max_{\theta} \ln p(D|\theta) \quad (9)$$

Assuming the existence of an unbiased estimator $\hat{\theta}(D)$, the CRLB is given by,

$$E\{[\hat{\theta}(D) - \theta][\hat{\theta}(D) - \theta]^T\} \geqslant J_d^{-1} \quad (10)$$

in which J_d is the 2×2 Fisher information matrix (FIM). Let $J_{d,ij}$ denotes the i^{th} row and j^{th} column element of J_d, then,

$$J_{d,11} = n^2 \sum_{i=1}^{N} \kappa_i a_i^2 d_i^{-4} (x_i - x)^2 \quad (11)$$

$$J_{d,12} = J_{d,21} = n^2 \sum_{i=1}^{N} \kappa_i a_i^2 d_i^{-4} (x_i - x)(y_i - y)$$

$$J_{d,22} = n^2 \sum_{i=1}^{N} \kappa_i a_i^2 d_i^{-4} (y_i - y)^2$$

where

$$\kappa_i = \frac{1}{8\pi\sigma^2} \sum_{l=0}^{L-1} \frac{\gamma_{i,l}}{p_{i,l}(\vec{\eta}_i, \theta)}$$

and

$$\gamma_{i,l} = [e^{-\frac{(\eta_{i,l} - a_i)^2}{2\sigma^2}} - e^{-\frac{(\eta_{i,(l+1)} - a_i)^2}{2\sigma^2}}]^2$$

Proof: See [2]

III. Proposed Iterative Source Location Estimation Algorithm

A. Sensor Selection Method

In this paper, we follow an iterative PCRLB approach while estimating the location of the source. Prior to the transmission of anchor sensor decisions, the fusion center has no information about the source location. To model this uncertainty, we assume the source location $\theta = [x, y]^T$ to be a random vector, which follows a diffuse uniform probability density function (pdf), namely

$$p(\theta) = \begin{cases} \frac{1}{b^2} & -\frac{b}{2} \leq x, y \leq \frac{b}{2} \\ 0 & otherwise \end{cases} \quad (12)$$

where b is a very large number, so that there is negligible prior information about the source location before the transmissions of anchor sensor decisions. As $b \to \infty$, a diffuse prior causes the posterior pdf of θ to be proportional to its likelihood function and, thus, the maximum a posteriori (MAP) estimate to coincide with the MLE. As a result, we use the MLE to estimate θ based on all the available data in each iteration.

In the first iteration $t = 1$, let the set of m anchor sensors $\mathbf{s}_m = \{s_1, s_2, ..., s_m\}$ send their data to the fusion center. Given the multi-bit decisions of the m anchor sensors, we have the ML estimate $\hat{\theta}_1^{MLE}$ as,

$$\hat{\theta}_1^{MLE} = \arg\max_{\theta} \ln p(D_1, D_2, ..., D_m|\theta) \quad (13)$$

Given θ, the FIM for this estimation problem has been provided by (11), denoted as $J_{d,1}(\theta)$. It is well known that the MLE is asymptotically unbiased, efficient, and Gaussian with its mean being the true value of the parameter, and covariance matrix provided by the CRLB matrix. Hence, we can use a Gaussian pdf to approximate the true pdf of the MLE,

$$\begin{aligned} p(\hat{\theta}_1|\theta) &\approx \mathcal{N}\left(\hat{\theta}_1; \theta, J_{d,1}^{-1}(\theta)\right) \\ &\approx \mathcal{N}\left(\hat{\theta}_1; \theta, J_{d,1}^{-1}(\hat{\theta}_1)\right) \end{aligned} \quad (14)$$

where $\mathcal{N}(\theta; \mu, C)$ denotes a Gaussian pdf with mean μ and the covariance matrix C. Also note that in the second step of (14), $J_{d,1}^{-1}(\theta)$ has been approximated by $J_{d,1}^{-1}(\hat{\theta}_1)$. Now let us derive the a posteriori pdf of θ once the MLE $\hat{\theta}_1$ is available

$$\begin{aligned} p(\theta|\hat{\theta}_1) &= \frac{p(\theta)p(\hat{\theta}_1|\theta)}{\int p(\theta)p(\hat{\theta}_1|\theta)d\theta} \\ &= \frac{1/b^2 p(\hat{\theta}_1|\theta)}{1/b^2 \int p(\hat{\theta}_1|\theta)d\theta} \\ &= \frac{p(\hat{\theta}_1|\theta)}{g(\hat{\theta}_1)} \end{aligned} \quad (15)$$

where

$$\begin{aligned} g(\hat{\theta}_1) &= \int p(\hat{\theta}_1|\theta)d\theta \\ &= \int |2\pi J_{d,1}^{-1}(\hat{\theta}_1))|^{-\frac{1}{2}} e^{-\frac{1}{2}(\theta - \hat{\theta}_1)^T J_{d,1}(\hat{\theta}_1)(\theta - \hat{\theta}_1)} d\theta \\ &= 1 \end{aligned} \quad (16)$$

Therefore, we have

$$\begin{aligned} p(\theta|\hat{\theta}_1) &= p(\hat{\theta}_1|\theta) \\ &= \mathcal{N}(\theta; \hat{\theta}_1, J_{d,1}^{-1}(\hat{\theta}_1)) \end{aligned} \quad (17)$$

During the second iteration $t = 2$, fusion center needs to activate non-anchor sensors that were idle in the previous iteration. The fusion center selects q sensors from the idle $(N-m)$ sensors. Then, there are $Comb(N - m, q)$ possible sensor activation strategies where $Comb(.)$ denotes the combination operation. We select q sensors that maximizes the posterior CRLB (PCRLB). At $t = 2$, the prior information regarding θ is provided through $p(\theta|\hat{\theta}_1)$. The total Fisher information matrix corresponds to the PCRLB is

$$J_2(k) = J_{p,2} + J_{d,2}(k), \quad (18)$$

where $k = 1, 2, .., Comb(N - m, q)$. Due to the Gaussian approximation made in (14) and (17), the prior information is

$$J_{p,2} = J_{d,1}(\hat{\theta}_1) \quad (19)$$

and $J_{d,2}(k)$ is nothing but the expectation of the standard FIM contained in the data provided by the q sensors that are desired to be activated, over the prior pdf of θ. Namely,

$$J_{d,2}(k) = \int J_{d,2}(k, \theta)p(\theta|\hat{\theta}_1)d\theta \quad (20)$$

in which $J_{d,2}(k,\theta)$ can be easily calculated using (11). The fusion center then decides on the sensor activation strategy k^* that minimizes the trace of $J_2(k)^{-1}$ which is basically the sum of the approximate source location variances for both x and y coordinates.

$$k^* = \arg\min_{k} \ \text{trace}\{J_2(k)^{-1}\} \tag{21}$$

The selected strategy k^* then activates q idle sensors $\{s_1', ..., s_q'\}$. At the end of the second iteration, the ML estimate of the source location is updated as,

$$\hat{\theta}_2^{MLE} = \arg\max_{\theta} \ln p(D_1, D_2, \cdots, D_m, D_1', \cdots, D_q'|\theta) \tag{22}$$

Again, after $\hat{\theta}_2^{MLE}$ is obtained, similar to (17) the a posteriori pdf of θ is

$$p(\theta|\hat{\theta}_2) \quad = \quad \mathcal{N}(\theta; \hat{\theta}_2, J_{d,2}^{-1}(\hat{\theta}_2)) \tag{23}$$

which in turn serves as the prior pdf for the third iteration. This procedure will be carried out recursively. At each iteration, the ML estimate based on available data and its corresponding covariance matrix provide the prior information for the next iteration, and an A-PCRLB is calculated in a manner analogous to (18).

B. Sensor Data Compression Method

In the preceding section, we introduced the sensor selection method. In this subsection, we describe the data compression method which further reduces the communication requirements.

Given the pdf of the location estimates, probability of receiving a certain multi-bit decision $D_j, (D_j \in \{0, 1, .., L-1\})$ from the sensor desired to be activated $s_j', j \in \{1, 2, .., q\}$ is expressed as,

$$p(s_j' = D_j) = \int p(s_j' = D_j|\theta)p(\theta)d\theta \tag{24}$$

In addition to this, the prior data $\mathbf{s}_p$ for the second iteration is $\mathbf{s}_p = \mathbf{s}_m$. Then for the second iteration, probability of receiving $s_j' = D_j$ given prior data has the form,

$$p(s_j' = D_j|s_1, ..., s_m) = \frac{\int p(s_j' = D_j|\theta)p(s_1, ..., s_m|\theta)p(\theta)d\theta}{\int p(s_1, ..., s_m|\theta)p(\theta)d\theta} \tag{25}$$

where we used the fact that given the source location, the sensor decisions are independent.

$$p(s_j' = D_j, s_1, ..., s_m|\theta) = p(s_j' = D_j|\theta)p(s_1, ..., s_m|\theta) \tag{26}$$

Ideally, using the information of $\{s_1, ..., s_m\}$ as side information, the multi-bit decision of s_j' can be compressed using $H(s_j'|s_1, ..., s_m)$ bits where,

$$H(s_j'|s_1, ..., s_m) = -\sum_{D_j=0}^{L-1} p(s_j' = D_j|s_1, ..., s_m) \log_2 p(s_j' = D_j|s_1, ..., s_m) \tag{27}$$

We have assumed the MLE estimation error is approximately Gaussian distributed. This assumption may not be accurate, since MLE is only asymptotically Gaussian. This is especially true in the first several iterations where the amount of data from anchor and first few non-anchor sensors is small. In order to overcome this, during the first few iterations fusion center requests M-bit data from all activated non anchor sensors until it reaches a satisfactory location estimate. Let $\sigma_{x_t}, \sigma_{y_t}$ be the standard deviations of the source locations obtained from J_t^{-1}. Then, once the standard deviation of the source location reach some specified accuracy level ($\sigma_{x_t}, \sigma_{y_t} < \gamma$), the fusion center requests each activated sensor to compress its data to B_j bits.

In here, B_j denotes the compressed quantized measurement of each activated sensor, which has to satisfy,

$$B_j \geqslant H(s_j'|s_1, s_2, .., s_m) \quad j \in 1, 2, ..., q. \tag{28}$$

If the estimation error satisfies the desired accuracy level for compression, the fusion center requests,

$$B_j = \lceil H(s_j'|s_1, s_2, ..., s_m) \rceil \tag{29}$$

bits from the sensors which are desired to be activated.

Each compressed sensor observation c_j is obtained from its actual M-bit observation D_j according to [5],

$$c_j = D_j \bmod 2^{B_j} \tag{30}$$

In this work, we assume that c_j is delivered to the fusion center without any error.

At the fusion center compressed sensor measurements are recovered as follows: First, the fusion center determines all the possible multi-bit decisions D_j' which yield c_j as a remainder after the modulo 2^{B_j} operation.

$$\forall D_j' = l : c_j = l \bmod 2^{B_j} \tag{31}$$

The multi-bit decision of each sensor is recovered with a simple maximum a posteriori probability (MAP) rule,

$$l^* = \arg\max_{l} p(D_j' = l|s_1, s_2, .., s_m) \tag{32}$$

In here, the posterior probability density function $p(D_j' = l|s_1, s_2, .., s_m)$ is defined as,

$$\frac{\int Q(\frac{\eta_{j,l} - \hat{a}_j(\theta)}{\sigma}) - Q(\frac{\eta_{j,l+1} - \hat{a}_j(\theta)}{\sigma})p(\mathbf{s}_m|\theta)p(\theta)d\theta}{\int p(\mathbf{s}_m|\theta)p(\theta)d\theta} \tag{33}$$

where $p(\mathbf{s}_m|\theta) = p(s_1|\theta)p(s_2|\theta)...p(s_m|\theta)$ and $[\eta_{j,l}, \eta_{j,l+1}]$ is the decision interval where sensor s_j' decides on l. At each iteration t, $p(\theta) = p(\theta|\hat{\theta}_{t-1}^{MLE})$ is the prior pdf and approximated as $\mathcal{N}(\theta; \hat{\theta}_{t-1}^{MLE}, J_{d,t-1}^{-1}(\hat{\theta}_{t-1}^{MLE}))$.

Then an iteration of the algorithm is completed. In Figure 2, we summarize our algorithm. As the amount of information about the source location increases, the estimation error on source location decreases. The algorithm continues until the A-PCRLB converges to the CRLB of the one-shot location estimator. The next section presents some illustrative examples.

IV. Simulation Results

In this section, we first describe the simulation settings and then present the numerical results.

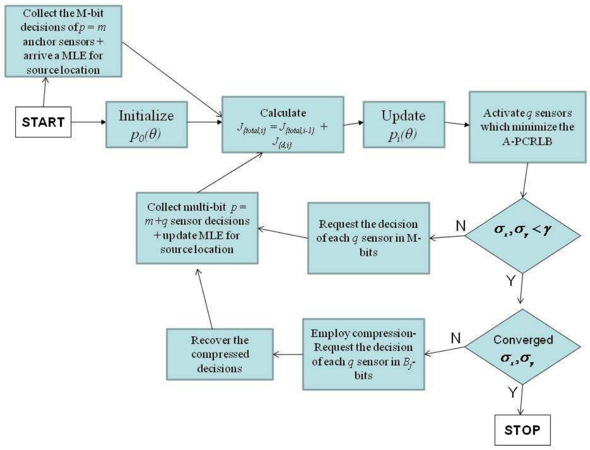

Fig. 2. Flow chart of the algorithm.

A. Assumptions

In our examples, we consider the source energy and signal decay factor as $P_0 = 25000$ and $n = 2$ respectively. The ML estimation for source location given in (9) is obtained through MATLAB's `patternsearch` optimization routine. $N = 19 \times 19 = 361$ sensors are deployed in a $100 \times 100m^2$ field and the sensors are deployed in a grid where location of each sensor is assumed to be known. The algorithm is initialized with $m = 4 \times 4 = 16$ anchor sensors and we assume the source is located at $(x, y) = (75m, 75m)$ as shown in Figure 1. We use $M = 5$ and $M = 6$ bits to represent the quantized measurements. The number of quantization level is then $L = 2^M$. We assume 0 as the minimum measurement and $\sqrt{P_0}$ as the maximum measurement captured from the source. 2^{L-1} points which divide $[0, \sqrt{P_0}]$ evenly are selected as the thresholds between the quantized decisions. The sensor measurements less than 0 and more than $\sqrt{P_0}$ are mapped to 0 and $L-1$ respectively. We select $\gamma = 1$ that is if the A-CRLB on σ_{x_t} and σ_{y_t} is below $1m$., the algorithm employs data compression as described in Section III.B, otherwise each activated sensor continues to transmit its data in M bits. In order to calculate (15), (21), (25) and (33), we use Monte Carlo numerical integration method [9] with 10^6 samples within the range $x_t \pm 3\sigma_{x_t}$ and $y_t \pm 3\sigma_{y_t}$.

B. Numerical Results

We first investigate the conditional entropy of each sensor given the measurements of the anchor sensors. In Figure 3, we present the conditional entropies of the sensors in the range $X \in [55m, 95m]$,$Y \in [55m, 95m]$. We calculate the conditional entropies of such 36 sensors given the M-bit decisions of the $m = 16$ sensors. Only, for this simulation, we select $E[x] = x$ and $E[y] = y$ and calculate the conditional entropies accordingly. Simulation results show that the sensors close to the actual source location have high entropies. As the sensor distance from the source location increases, quantized observations of the sensors tends to zero and whatever the side information is, conditional entropy of such a sensor decreases and goes to zero.

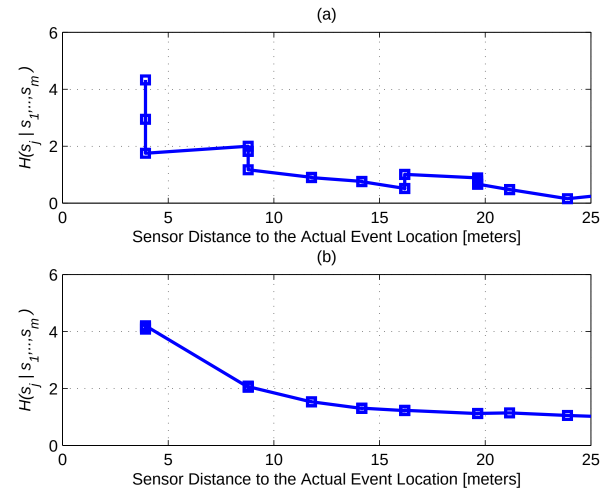

Fig. 3. Conditional Entropy of idle sensors in the field given the multi-bit decisions of the anchor sensors at the beginning of the first iteration. (a) M = 5 bit, (b) M = 6 bit

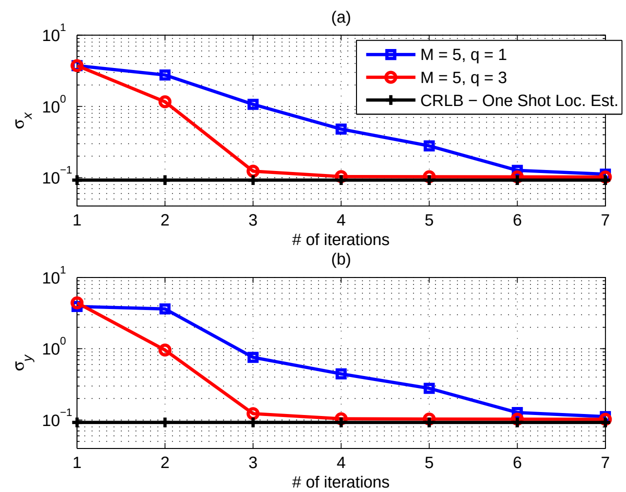

Fig. 4. M = 5, Black straight line with star markers is the CRLB for one shot location estimator. A-CRLB at several iterations (Straight blue line with square markers and dashed red line with circle markers are the mean of (a) : σ_x and (b) : σ_y for $q = 1$,$q = 3$ sensor activations after 5 different trials.

In Figure 4, we compare our iterative scheme with the one shot location estimator where each of the 361 sensors sends $M = 5$ bit quantized information to the fusion center at the same time. In Figure 4, we plot the mean of 5 different trials of our algorithm with $q = 1$ and $q = 3$ sensor activations per iteration. Simulation results show that, using $q = 1$ sensor activation/iteration the A-CRLB achieved by the iterative algorithm reaches the CRLB of the one shot location estimator in about 7 iterations which requires 97 bit transmission to the fusion center until the convergence (In here

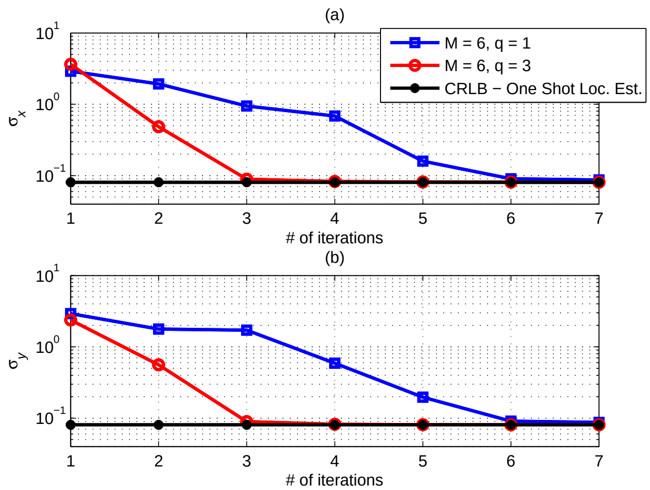

Fig. 5. M = 6, Black straight line with star markers is the CRLB for one shot location estimator. A-CRLB at several iterations (Straight blue line with square markers and dashed red line with circle markers are the mean of $(a) : \sigma_x$ and $(b) : \sigma_y$ for $q = 1$,$q = 3$ sensor activations after 5 different trials.

$16 \times 5 = 80$ bit transmissions are due to the the transmission of anchor sensor decision at the first iteration). On the other hand, activating $q = 3$ sensors per iteration reduces the convergence time significantly and requires 4 iterations requiring on the average transmission of 124.6 bits. When $M = 5$, the one shot estimator requires $M \times N = 5 \times 361 = 1805$ bit transmissions to the fusion center. In Figure 5, we simulate the $M = 6$ case. With $q = 1$ sensor activation/iteration the convergence is reached at 6^{th} iteration and with $q = 3$ sensor activation/iteration the convergence is reached at 3^{rd} iteration. For $M = 6$ bit quantization, one-shot estimator requires $M \times N = 6 \times 361 = 2166$ bit transmissions to the fusion center. On the other hand, until convergence, the iterative algorithm requires 120 and 126 bits for $q = 1$ and $q = 3$ sensor activations/iterations respectively. The communication and delay performance is summarized in Table I.

Note that the conditional entropies are calculated based on the current location estimates (x_t, y_t). As M increases, the range of a quantization interval $[\eta_{j,l}, \eta_{j,l+1}]$ decreases significantly. Therefore, we require a more accurate location estimate to employ data compression and select a much lower value for γ. Otherwise based on the current location estimates (x_t, y_t), the data recovery process may yield misleading results. Instead of employing a threshold to ensure a satisfactory location estimation, one other way to solve this problem is to add some additional bits to the calculated conditional entropy defined at Eq. (22). But in this case, first iterations of the algorithm may require more guard bits as compared to the rest of the iterations as a result of large standard deviation of the location estimates.

V. Conclusions

In this work, we presented an iterative source localization scheme where we first estimated the source location through a small number of anchor sensors. Then we activate a number of idle sensors in an iterative manner which minimize an approximate PCRLB. Based on the accuracy of the location estimates we calculate an approximate probability distribution of the location estimates and compute the conditional entropies of the activated sensors. Simulation results show that the proposed iterative scheme approaches the CRLB of the one shot location estimate within few iterations while significantly decreasing the communication requirements.

TABLE I
Communication/Delay Comparison

	Converged at Iteration	Total Number of Transmitted bits until convergence (on the Average)
M = 5, One-Shot	1	1805
M = 5, q = 1	7	97
M = 5, q = 3	4	124.6
M = 6, One-Shot	1	2166
M = 6, q = 1	6	120
M = 6, q = 3	3	150

Acknowledgment

In this work, Engin Masazade is financially supported by The Scientific and Technological Research Council of Turkey (TUBITAK) under Research Abroad Support Scheme. The work of Ruixin Niu and Pramod K. Varshney was supported in part by AFOSR under grant FA-9550-06-1-0277. The work of Mehmet Keskinoz was supported by TUBITAK under grant 105E161.

References

[1] X. Sheng and Y. H. Hu, Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks, IEEE Trans. Signal Process., vol. 53, no. 1, pp. 4453, Jan. 2005.
[2] R. Niu and P.K. Varshney, "Target Location Estimation in Sensor Networks with Quantized Data," IEEE Transactions on Signal Processing, pp 4519-4528, December 2006
[3] L. Zuo, R. Niu, and P.K. Varshney, "Posterior CRLB Based Sensor Selection for Target Tracking in Sensor Networks," Proceedings of the 2007 IEEE International Conference on Acoustics, Speech, and Signal Processing, II 1041-1044, Honolulu, Hawaii, April 2007.
[4] O. Ozdemir, R. Niu and P.K. Varshney, "Adaptive Local Quantizer Design for Tracking in a Wireless Sensor Network," Proceedings of the 42nd Annual Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, October 2008
[5] J. Chou, D. Petrovic, and K. Ramchandran. A Distributed and Adaptive Signal Processing Approach to Reducing Energy Consumption in Sensor Networks. In Proc. of the 22nd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM), 2003
[6] Z. Xiong, A. Liveris, and S. Cheng, Distributed source coding for sensor networks, IEEE Signal Processing Mag., vol. 21, pp. 8094, Sept. 2004.
[7] D. Slepian and J. K. Wolf, Noiseless encoding of correlated information sources, IEEE Trans. on Inform. Theory, vol. IT-19, pp. 471480, July 1973.
[8] S. Venkatesh, and R. M. Buehrera, "Multiple-access insights from bounds on sensor localization", Pervasive and Mobile Computing Volume 4, Issue 1, February 2008, Pages 33-61
[9] R. E. Caflisch, Monte Carlo and quasi-Monte Carlo methods, Acta Numerica vol. 7, Cambridge University Press, 1998, pp. 1-49.