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Energy Efficient Approach to Target Localisation in Wireless Sensor Networks

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ABSTRACT

This paper investigates a general class of centralized-distributed optimization algorithm for in-network target localization in wireless sensor networks, WSNs. The main objective is reducing the amount of energy and bandwidth used for computations as well as for communications. The proposed algorithm is based on incremental gradient optimization technique. Applying results from signal detection theory, a criteria for sensor self activation and participation is formulate. The optimization scheme is extended to the case wherein signal measurements are corrupted with additive white Gaussian noise. Results demonstrated the potential of the proposed algorithm for applications in practical wireless sensor networking.

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1. INTRODUCTION

A wireless sensor network often performs monitoring tasks such as detection, localization, and tracking of one or more targets in the sensor field. Sensors are battery powered and have limited wireless communication bandwidth. Therefore, efficient signal processing algorithms that consume less energy for computations and less bandwidth for communications are needed [1]. Existing source localization techniques make use of three types of physical measurements: time of arrival (TOA), direction of arrival (DOA), and received signal strength. DOA is estimated by exploiting the phase difference measured at receiving sensors [2]–[6] and is applicable when the source emits a narrowband signal. TOA is suitable for broadband source localization and has been extensively investigated in [7] - [12]. It requires accurate measurements of the relative time delay between sensor nodes. It is known that the intensity or the energy of signal attenuates as function of distance from the target. Using this property, an energy-based source localization methods are reported in [13] for locating single target in an open sensor field.

This paper presents a solution to the position estimation problem using convex optimization: If one node can communicate with another, a proximity constraint exists between them. As a typical example, if an RF system can cover 20 m and two nodes are in communications; their separation must be less than 20 m. Therefore, sensor networks can be seen as a graph with n nodes at the vertices (each node having a Cartesian position) and with communication distance constraints as the edges. The positions of the first m (anchor) nodes are known ($x_1, y_1 \ldots x_m, y_m$) and the remaining n-m positions are unknown. The problem of finding the positions of the remaining nodes ($x_{m+1}, y_{m+1}, \ldots x_n, y_n$) such that the proximity constraints are satisfied, given a few anchor nodes (equipped with GPS or placed deliberately) and relative distance information between the nodes, is known as the position estimation or localization problem.

The position estimation methodology developed in this paper requires mixed centralized and distributed computations. Namely, all nodes must communicate their connectivity information to a single fusion node (center) to solve the optimization problem. The basic idea is to reduce the amount of communication and energy resource consumptions as will be explained later. An outline of the paper is as follows. Section 2 provides background on previous localization works. In Section 3 we first consider the sensing model, and then, we present a statement of the problem under consideration. Section 4 presents an approach to provide estimates for target localization based on mix of distributed and centralized iterative descent computations. Section 5, presents a criteria for sensor activation and shows its impact on resource energy savings. Section 5 presents numerical examples to illustrate the approach, and Section 6 presents summary and conclusions

2. RELATED WORK

An extensive research has been done on localization for WSNs. A general survey can be found in [14], [15], [23]. In these literatures, the authors discuss most important localization techniques and critique those techniques. However, there are some existing systems which use localization techniques [16]. These techniques give new directions in WSN localization as these schemes give high accuracy at low communication and computation costs. In [17], an improvement on these results by using a multidimensional scaling approach is presented. Another approach to the localization problem depends on hop counting technique. To provide localization in networks wherein fusion node density is low, centralized hop-counting technique propagates location announcements throughout the network. In [18], a technique based on distance vector routing is presented. Each node maintains a counter denoting the minimum number of hops to each fusion node, and updates that counter based on messages received. Another centralized localization approaches depend on sensor nodes transmitting data to fusion node, where computation is performed to determine the location of each node. As an example, in [19, 22], a centralized technique using convex optimization to estimate positions based on network connectivity constraints given some anchor nodes with known positions is developed. In the following section we first introduce the sensing model. Then we describe a detailed formulation of the problem.

3. SENSING MODEL AND PROBLEM FORMULATION

3.1. Sensing Model

Most of previous work in the literature adopted a binary disc sensing model, i.e., a source is sensed with probability 1 if it is within the sensing radius of at least one sensor, or with probability 0 otherwise. Such models capture the property that signal strength decays as it travels from source (target) to the sensor nodes (SNs). As such, the probability such that a SN detects a signal decreases as the distance between the target and the SN increases. In this respect, we use the signal strength-based, probabilistic sensing model described in [20]. According to [20], the received signal strength, $P_r(d)$, at a particular location with d separation between the target and the sensor, is the difference between the transmitted signal strength, $P_t(O)$, at the source O, and the path loss, PL(d).

$$P_r(d) = P_t(O) - PL(d)$$

$$PL(d) = PL(d_0) + 10\, n \log\left(\frac{d}{d_0}\right) + X_\sigma$$

where X_σ is a zero mean Gaussian distributed random variable (in dB) with standard deviation σ, d_0 is a close-in radial distance, n is the path loss exponent, $PL(d_0)$ is the average path loss at d_0, which can be obtained based on either experimental measurements or on a free space assumption to d_0 [21].

Let P_s denotes the sensing probability provided by a given SN to the point of interest, O. Assuming that the SN can only successfully detects a signal with strength greater than a given threshold γ, then, we have,

$$P_s = P_b(P_r(d) > \gamma) = Q\left(\frac{\gamma - P_r(d)}{\sigma}\right) \quad (1)$$

where, Q-function is defined as: $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-z^2} dz$.

3.2. Problem Formulation

In order to estimate the location of a given target, this involves gathering a collection of $\{X, Y, d\}$ values, where d, represents an estimated distance from the target to the sensor at (X, Y). The estimated distance d, stems from signal strength measurements. In the ideal case, where the distances are not subjected to any measurement noise or errors, these $\{X, Y, d\}$ values map out a parabolic surface,

$$d^2 = (X - X_t)^2 + (Y - Y_t)^2 \quad (2)$$

Gathering several $\{X, Y, d\}$ values, and solving for (X_t, Y_t) is a nonlinear least squares problem that accounts for determination of the target coordinates,

$$(X_t^{\wedge}, Y_t^{\wedge}) = \text{arg.} \min_{(X_t^{\wedge}, Y_t^{\wedge})} [d^2 - \sqrt{(X - X_t)^2 + (Y - Y_t)^2}\,]^2 \tag{3}$$

This nonlinear problem, usually involves some iterative searching technique, such as Newton method, to get the solution. In the following section, we use the gradient descent nonlinear searching method, which lends itself to distributed calculations as will be explained latter.

4. AN ENERGY EFFICIENT DISTRIBUTED-CENTRALIZED LOCALIZATION SCHEME FOR WSNs

A major challenge in developing WS systems and algorithms is that, transmitting data between SNs or from each SN to a fusion center may place significant drain on communication and energy resources. This section, presents an approach based on mix of the distributed and centralized in-network processing which is seen to, significantly, decreases the communications and energy resources consumed. The basic idea can be explained as follows. Consider a WSN comprised of n nodes uniformly distributed over a square area, each of which collects m measurements. The objective is to estimate the position of a given target. Let us consider first, the totally distributed scenario: in this case, in a single iteration, each SN makes a single transmission – the current position estimate – to its nearest neighbor. Thus, the average number of transmissions is N (n) =O (nm) × K, where K is the number of cycles (iterations) required for the desired level of accuracy. Alternatively, consider the all centralized approach wherein each sensor transmits its measurements to a fusion center. The number of transmissions in this case is N (n) = O (nm) while all necessary iterations, K, are carried out at the fusion center. However, it is well-known that the amount of energy consumed for a single wireless transmission of one bit can be many orders of magnitude greater than the energy required for a single local computation. As can be seen, the centralized approach is much more advantageous than the distributed processing from the perspective of energy especially if m and n are large.

In the following we present our centralized-distributed localization scheme in which we assume that each sensor knows its coordinates and that the received signal strength measurements from SN_itakes the form,

$$r_i = s_i + w, \tag{4}$$

where, w is a white Gaussian noise process. At this point, our objective is not that each SN transmits a collection of "raw" energy measurements to the fusion node, but rather it transmits its estimate of the target location. Certainly, transmitting the estimates rather than the statistical data will reduce the energy consumption even further by reducing the number of messages per transmission (m). In this respect, as mentioned in section 3, we use the gradient descent nonlinear searching method which lends itself to distributed calculations. Now, assuming an isotropic energy propagation model for the j-th received signal strength measurements at SN_i, equation (4) becomes,

$$r_i = \frac{G}{\|z - d_i\|^{\beta}} + w, \tag{5}$$

where, G is the power emitted from the source, z is the unknown target position, d is the sensor position (Equ. (2)), β is the attenuation exponent.

Now, we present the distributed phase of our scheme, a least squares estimate for the target's location is found by solving,

$$F_i(z) = \text{arg.} \min_z [r_i - \frac{G}{\|z - d_i\|^{\beta}}]^2 \quad , i{=}1, 2 \ldots, \tag{6}$$

the gradient of $F_i(z)$ is found,

$$\nabla F_i(z) = \frac{2\beta G}{\|z - d_i\|^{\beta+1}} \left(r_i - \frac{G}{\|z - d_i\|^{\beta}} \right) \tag{7}$$

Without loss of generality, assume that sensors have been numbered i = 1, 2. . . n according to their order in the sensing field. Sensor i receives the power measurements r_i from the target, computes an estimate of the target position z according to,

$$z_i^k = z_i^{k-1} - \alpha \nabla F_i(z_i^{k-1}) \tag{8}$$

where, α is the step size. The iterations begin with arbitrary initial condition z_i^0 and after some iteration, we get $z_i^k = z_i^{k-1}$.

At this point, assuming that "active sensors" are those which satisfy the condition stated by Equ. (1) (will be explained in the following section) and, that each one has computed its local estimate for the target position z, transmits the estimate to the fusion node. This summarizes the distributed phase of our algorithm.

In the centralized phase, the fusion node computes the global optimal positioning estimate. To achieve this goal, recall that equation (2) is equivalent to solving the following set of equations,

$$z_i^2 = (X_i - X_t^{\wedge})^2 + (Y_i - Y_t^{\wedge})^2 \quad , i{=}1, 2 \ldots L, \tag{9}$$

where, (X_i, Y_i) is the (known) sensor coordinates, $(X_t^{\wedge}, Y_t^{\wedge})$ an estimate for the target coordinates and L is the number of active sensors. Expanding Equation (9) around $(X_t^{\wedge}, Y_t^{\wedge})$ using Taylor series yields,

$$F(X_t^{\wedge} + \Delta X_t^{\wedge}, Y_t^{\wedge} + \Delta Y_t^{\wedge}) \approx F(X_t^{\wedge}, Y_t^{\wedge}) + \frac{\partial F(X_t^{\wedge}, Y_t^{\wedge})}{\partial x} \Delta X_t + \frac{\partial F(X_t^{\wedge}, Y_t^{\wedge})}{\partial y} \Delta Y_t \quad (10)$$

From equations (9), (10), we find,

$$\frac{\partial F(X_t^{\wedge}, Y_t^{\wedge})}{\partial x} = \frac{X_i - X_t^{\wedge}}{z_i^{\wedge}}, \quad \frac{\partial F(X_t^{\wedge}, Y_t^{\wedge})}{\partial y} = \frac{Y_i - Y_t^{\wedge}}{z_i^{\wedge}}, \quad z_i^{\wedge} = \sqrt{(X_i - X_t^{\wedge})^2 + (Y_i - Y_t^{\wedge})^2}$$

Now define $Z_i = Z_i^{\wedge} - \left(\frac{X_i - X_t^{\wedge}}{z_i^{\wedge}} \Delta X_t + \frac{Y_i - Y_t^{\wedge}}{z_i^{\wedge}} \Delta Y_t\right)$,

and, $\Delta Z_i = Z_i^{\wedge} - Z_i$, $a_{xi} = \frac{X_i - X_t^{\wedge}}{z_i^{\wedge}}$, $a_{yi} = \frac{Y_i - Y_t^{\wedge}}{z_i^{\wedge}}$

Then, we have the following set of linear equations,

$$\Delta Z_i = a_{xi} \Delta X_t + a_{yi} \Delta Y_t, \qquad i = 1, 2, \ldots L$$

Therefore, the true target position can be obtained by solving the following matrix equation,

$$\Delta \varepsilon = (R^T R)^{-1} R^T \Delta Z$$

where

$$R = \begin{bmatrix} a_{x1} & a_{y1} \\ a_{x2} & a_{y2} \\ \cdots & \cdots \\ \cdots & \cdots \\ a_{xL} & a_{yL} \end{bmatrix}, \qquad \Delta Z = \begin{bmatrix} \Delta Z_1 \\ \Delta Z_2 \\ \cdots \\ \Delta Z_L \end{bmatrix}, \qquad \Delta \varepsilon = \begin{bmatrix} \Delta X_t \\ \Delta Y_t \end{bmatrix}$$

Having obtained $\Delta \varepsilon$, we can obtain the true target coordinates,

$$X_t = X_t^{\wedge} + \Delta X_t, \qquad Y_t = Y_t^{\wedge} + \Delta Y_t \quad (11)$$

As can be seen, the two phases comprise a distributed-centralized mixed system, consisting of custom operating systems running on both the sensors and the fusion center and, hence, suggests a concrete example of a practical sensor network. Another aspect of this problem is considered in the following section

5. SENSOR SELF ACTIVATION

It is important to investigate the distribution of the signal amplitude received at each sensor node. Equation (1), states the fact that,

$$P_s = P_b(P_r(d) > \gamma) = Q\left(\frac{\gamma - P_r(d)}{\sigma}\right)$$

Therefore, the threshold γ of this binary detection scheme should not be too high or too low, in order to convey useful information about the target position. Given this condition, we derive the threshold γ which returns a given detection probability,

$$\gamma = P_r(d) + \sigma P_s^{-} \quad (12)$$

where $P_s^{-} = Q^{-1}\left(\frac{\gamma - P_r(d)}{\sigma}\right)$,

and from Equ. (5), assuming $\beta = 2$, we obtain the corresponding distance, from the target, at which a given probability of detection is guaranteed,

$$d_i(P_r(d)) = \sqrt{\frac{G}{P_r(d)}} \quad (13)$$

Hence, based on the sensor's location (Equ. (11)), and using Equ. (12) and (13), at a given probability of detection, each SN can make its own local decisions as to: act and participate in the position calculations procedures or abstain. Its decision is made independently without cooperating with one another. That is, each SN will compare the actually received power with that required to achieve a given probability of detection and, hence, decides to participate in the target positioning scheme or to abstain otherwise. As such, each sensor is restricted to compute and communicate its estimation if and only if, the received power satisfies Equs. (12) and (13). Certainly, this would make the target localization procedures much more communication and computation efficient by placing limits on the amount of undesirable computations and data transmissions by the sensor networks. The performance of the target localization system proposed in this paper is validated in the next section

6. NUMERICAL RESULTS

Consider a scenario in which 9- sensor nodes are randomly placed in a 10 m ×10 m region among which 4 of them are considered active according to Equs. (12), (13). Figure (1) shows the locations of the sensor nodes along with a stationary target.

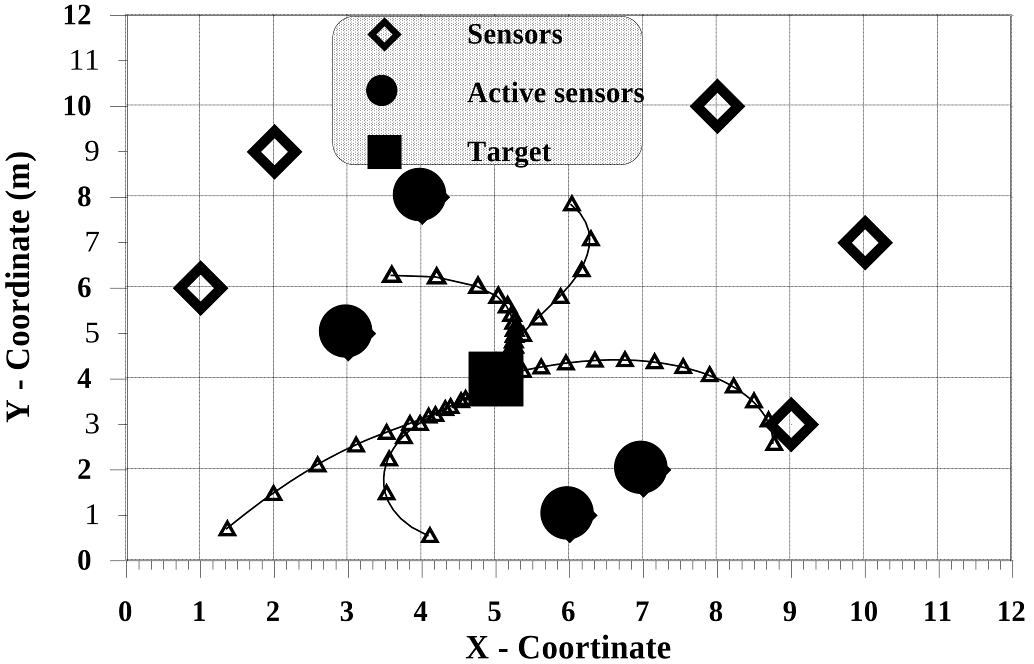

Figure 1. Target localization: iterations

We assume that each SN has the ability to sense and estimate its distance to the target by performing simple computations, Equ. (8), and communicates its estimate directly to the fusion node which computes the target coordinates using equations (11). As show in Figure 1, the distributed / centralized algorithm returns the true target coordinates using different initial starting points. Next we show the performance of the algorithm when the target moves. In this scenario, a target moves across a 20 m × 20 m sensing field, taking the dashed line trajectory as displayed in Figure 2. The target moves from left to right across the field. At each point in time, sensors within a distance determined by Equations (12), (13), of the source are activated and participate in the target localization estimation based on their signal strength measurements. In this case, active nodes estimate the target location once and this position estimate is then used as the initial estimate at the next point in time.

In the next example we replace the active sensor AS-4 by an arbitrary sensor nodes (PS_k, k= 1, 2 . . . 5) to participate, PS, in the target positioning procedure as depicted in Figure 3. The objective is to investigate the effect of ignoring the conditions stated by Equs. (12), (13) on the number of iterations required to converge to the true position of the target. The result is depicted in Figure 4. As can be seen, participation of sensors with relatively low received powers tends to result in larger number of iterations before the algorithm converges to the true target location. Next, the results in Figure 4, (no noise case) is compared with other cases wherein additive white Gaussian noise with different variances are add to the sensor measurements as indicated by Equ. (5). As can be seen from Figure 5, the algorithm is sensitive to errors, i.e. inaccuracies in the power measurements due to noise and, hence, it relies on additional iterations independent of the initial starting points or the value of the step size α in Equ. (8). Next, in Figure 6, we show an example on the relationship between the target detection probability and the sensor activation threshold and,

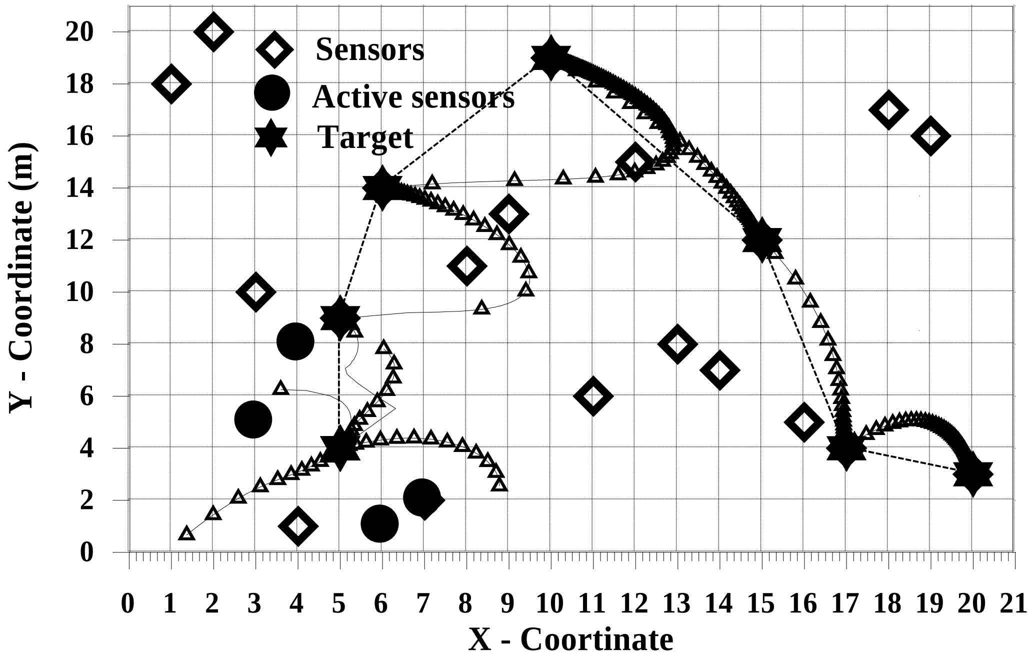

Figure 2. Target localization: target moved

In Figure 7, we repeat but for the detection range d. These figures are intended for the WSN designer. For instance, a significant savings in the resource energy can be inferred from the connection-imposed proximity constraints depicted in Figure 6, so that some sensor in the sensing field are allowed to refrain from participating in the target positioning computations and transmissions. On the other hand, the value of the sensor density required for a random sensor deployments in the sensing field can be inferred from figure 7 such that a predefined sensing probability is guaranteed.

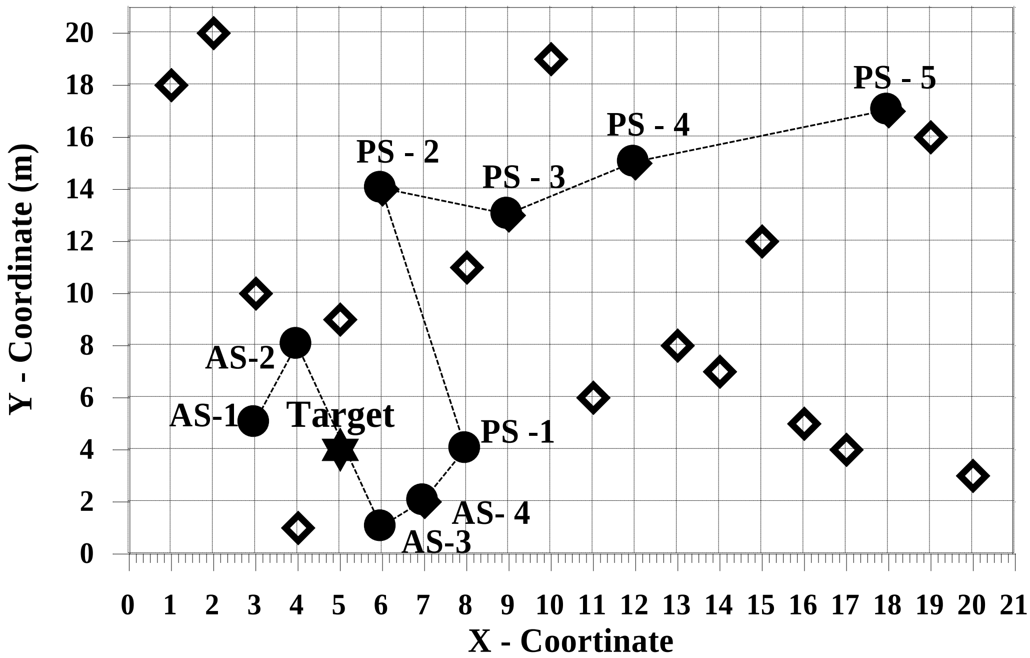

Figure 3. Target localization: far sensor participation

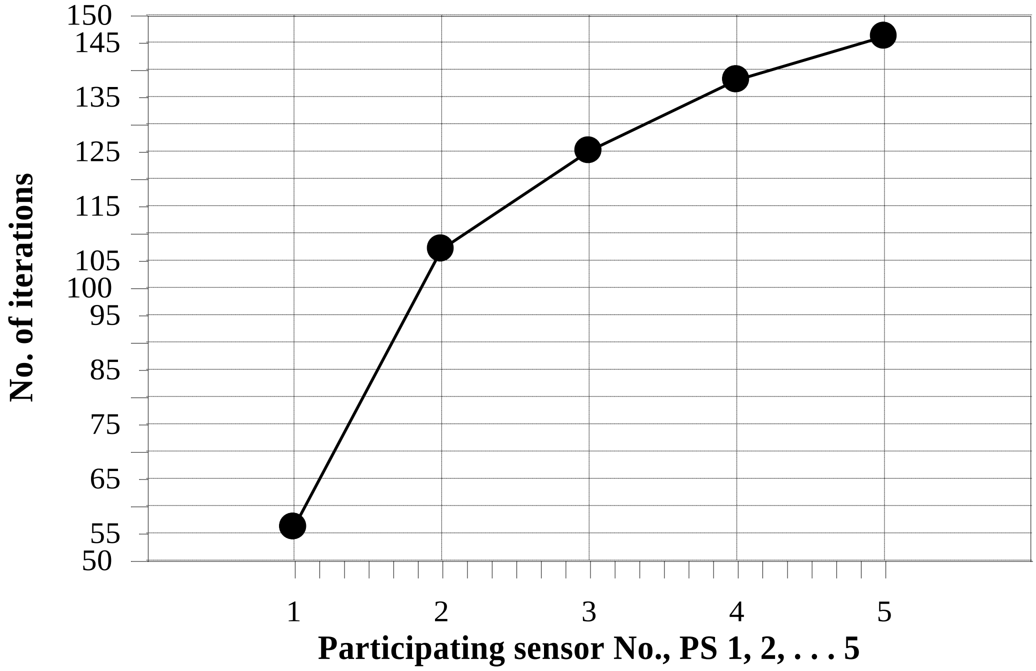

Figure 4. Effect of far sensor participation

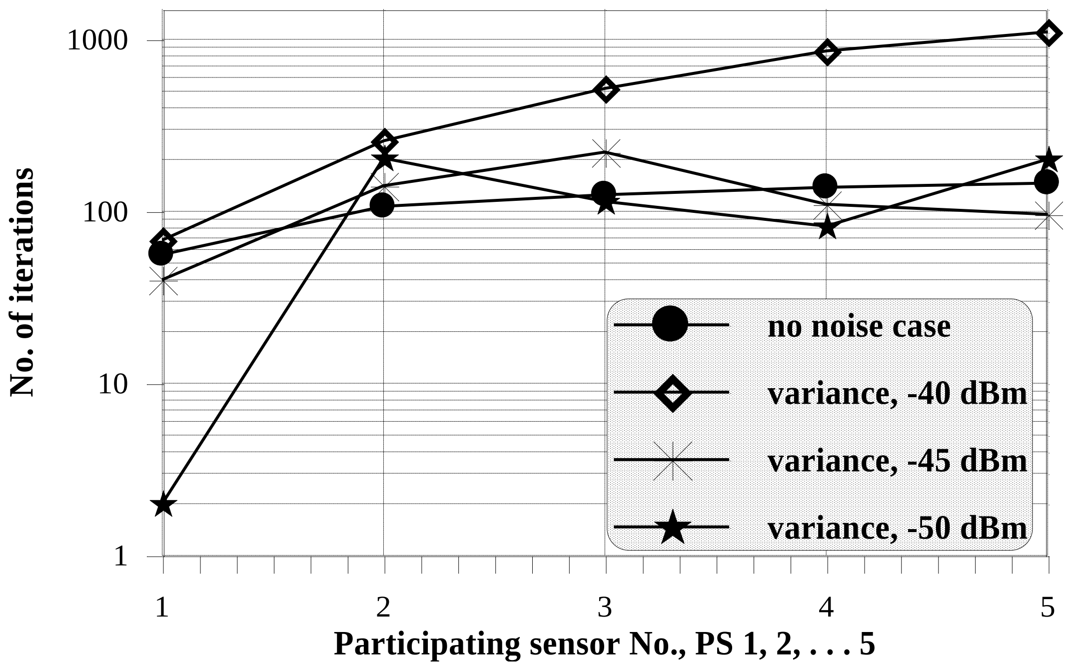

Figure 5. Effect of noise on target localization

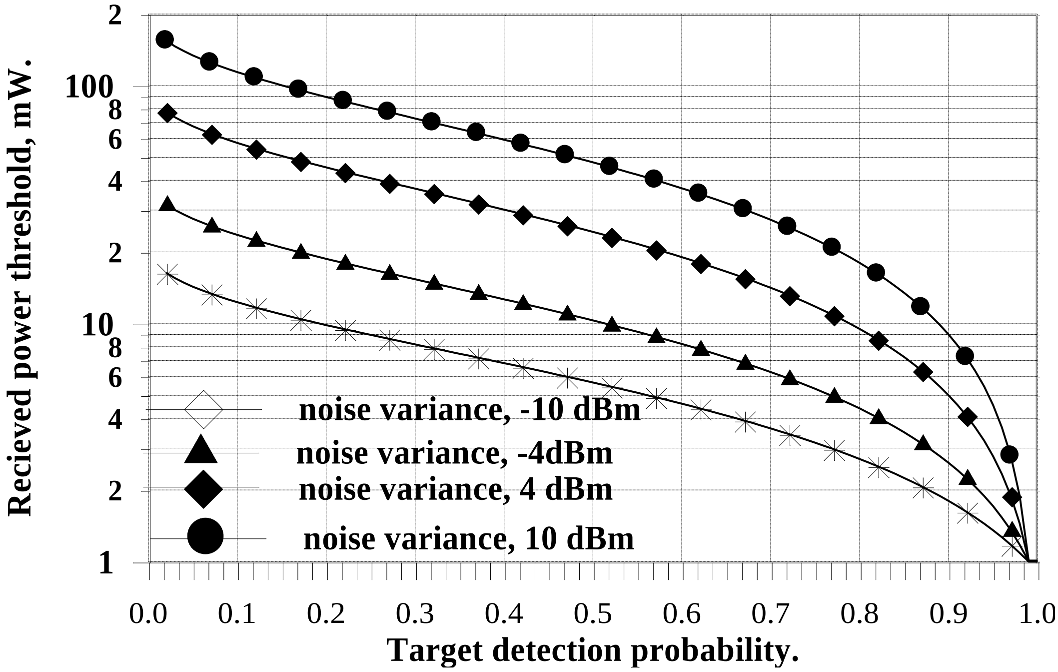

Figure 6. Received power thresholding

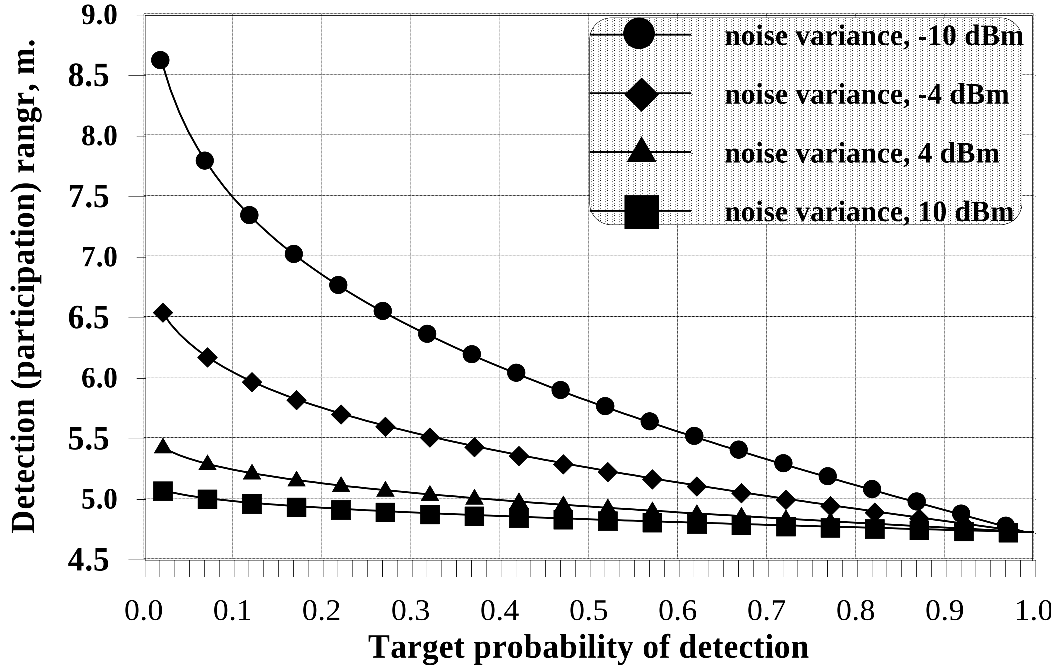

Figure 7. Sensor ranging

7. SUMMARY AND CONCLUSIONS

We have presented a distributed-centralized model for target localization in wireless sensor networks. In this model, all sensor nodes make their local active (abstain) decisions independently without cooperating with one another. Since we are considering bandwidth-constrained WSNs, i.e., the communication channels between the sensor nodes and the fusion centers are bandwidth-constrained, each sensor is restricted to sending its (distance to the target) estimation to the fusion center rather than sending statistical parameters of its measurements. On the other hand, as the performance of the target sensing system is characterized by its corresponding probability of detection. All sensor nodes that are within activation condition can participate in the target positioning procedures. This is achieved using incremental gradient optimization scheme. Then, sensor nodes transmit their local decisions over parallel channels to the fusion center. The fusion center, in turn, computes the globally optimal target coordinates using an approximation to the least squares optimization problem. The approach being proposed is verified through set of numerical examples. Results demonstrated the potential of the algorithm for practical interest in sensor networking.

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