An RSSI Based Localization Scheme for Wireless Sensor Networks to Mitigate Shadowing Effects

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***Abstract-* We propose a RSSI based localization scheme for wireless sensor networks that mitigates the effects of shadowing caused by obstacles that are scattered in the field of operation. The proposed scheme applies a spatial correlation mechanism to eliminate RSSI signals that are affected by obstructions. The effectiveness of the proposed scheme is validated using simulations as well as some initial experimental results.**

***Keywords:* Wireless sensor networks, localization, moving beacons, obstacles.**

I. Introduction

In the last decade, a significant amount of research have been directed towards enabling wireless sensor networks (WSN) to be a viable and cost-effective solution for distributed monitoring tasks. WSNs can utilize multi-modal information from embedded sensors, perform onboard processing, and apply distributed processing for monitoring applications that include environmental monitoring, health monitoring, security, industrial control, and many others. They are also easy to deploy and can be programmed to adapt to changing conditions. The main challenge towards developing long-term applications with WSNs is that the sensor nodes have limited computational, communication, and energy resources, and hence, all tasks must be designed with these constraints.

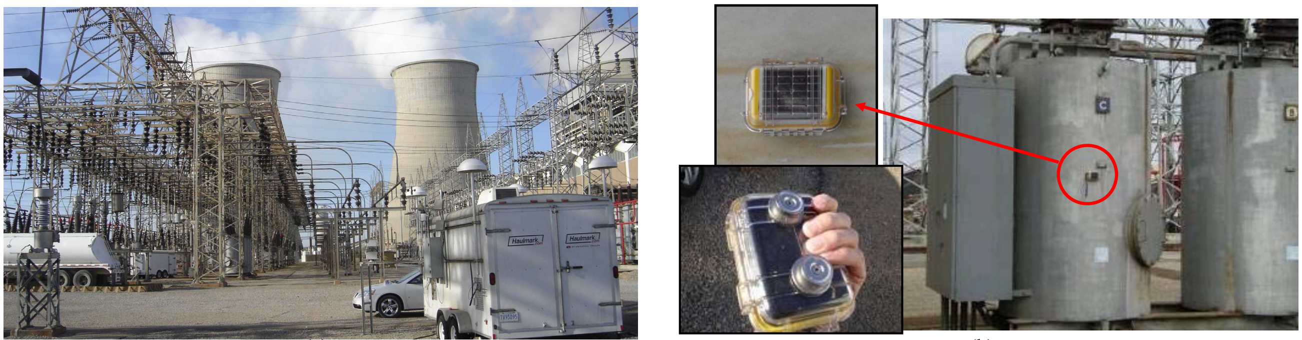
Position estimation of the wireless sensor nodes, popularly termned as localization, in WSNs is a critical task that is required for most applications as well as for aiding many networking protocols (e.g. routing) in WSNs. Despite the tremendous advancements made on the development of geographical positioning systems, this task requires special solutions for WSNs because state-of-the art positioning systems, such as GPS, are not viable for WSNs due to cost and energy constraints. Furthermore, GPS requires satellite signals, which may not be available in sensor nodes that do not have clear view of the sky. Consequently, significant research efforts have been reported for the development of cost-effective localization schemes for WSNs that can operate under the constraints of resources in the sensor nodes.

A popular approach for localization that can be applied without requiring additional hardware in wireless sensor nodes is the use of distance estimates of the nodes from known locations (beacons) using the RF received signal strength indicator (RSSI). However, RSSI is an inaccurate measure of distance due to irregularities of wireless signal propagation. Hence, much of the work on RSSI based localization techniques have been directed towards developing methods for minimizing errors of such estimates. Typically this can be achieved by multilateriation, which involves combining RSSI information from a number of beacons that is greater than the minimum number required for localization using accurate distance estimates (viz. three beacons for localization on a plane and four beacons for localization over a three dimensional space) [1]. Our research is motivated by the fact that multilateration with RSSI based distance estimates is severely affected by shadowing effects that cause some of the RSSI measurements to be uncharacteristically erroneous than others. We propose a scheme that applies a simple spatial correlation mechanism to select a subset of a (large) number of beacons signals to perform multilateration. The idea behind this approach is that for any node in a typical WSN deployment, some of the beacon signals will be unobstructed, and hence distances estimated from their RSSI values will be less erroneous than others. Consequently, multilateration with RSSI measurements from those signals would provide higher accuracy of the node location. We demonstrate from simulation studies that such an approach reduces the localization error compared to one that applies multilateration to all beacon signals together. We also present some results obtained from an experimental testbed to show the effectiveness of the proposed localization scheme.

The rest of the paper is organized as follows. In section II, we summarize the related work. Details of the motivation for this work and the problem statement are provided in section III. Section IV describes our localization scheme in detail. Performance evaluations from simulations and from some basic experimental data are discussed in section V. We conclude our paper section VI.

II. Related Work

Localization schemes for WSNs can be broadly classified into two: range-based and range-free localization schemes. Range-based localization schemes [2], [3], [4], [5] use RSSI, angle-of-arrival (AOA), time of arrival (TOA), or time difference of arrival (TDOA) to measure the distance or angle between a beacon and an sensor node and then use trilateration or triangulation to estimate the sensor nodes position. These approaches are effective as long as the distance or angle estimates are not too inaccurate. Range-free schemes [6], [7], [8] do not use range measurements to estimate sensor node location. However, these schemes do not attempt to



(a) (b)

Fig. 1. (a) View of the Paradise substation, where the *ParadiseNet* was deployed. (b) One of the wireless sensor nodes for circuit-breaker monitoring.

provide precise location estimates. For instance, some range free localization schemes use communication ranges (or RF based proximity method) to estimate the region where a sensor node is located.

The scheme widely used to reduce the error in range based localization techniques using RSSI is the linear least square method, which determines the estimated location that minimizes the average error from all reference points. The error margin with this method reduces with increasing number of anchors used for multilateration. However, the problem that presents itself is that in a large and obstructed sensor network, an unknown node may not receive a sufficiently large number of beacon signals from anchors. The result of this is insufficient error minimization. One approach to overcome this problem is to apply iterative multilateration [1]. However, this method suffers from the drawback of propagating errors throughout the sensor network. Another method used in solving the problem mentioned is by collaborative multilateration but this method involves solving for all unknown positions simultaneously resulting in a non-linear optimization problem. Though there are ways to solve this, like the Kalman filter, they involve significant computation as well as communications costs.

Mobile beacons are popularly used in many sensor localization schemes to provide the necessary distance or angle estimates. An example is the work by Bin Xiao et al. [6], who proposed a distributed localization scheme using a mobile beacon. A sensor node is assumed to be in a region called Arrival and Departure Overlap (ADO) formed by the intersection of the arrival constraint area and departure constraint area constructed by the beacon signals as the beacon arrives and departs the sensor nodes sensing range. C. Wang et al. [9] proposed the MRTP algorithm which uses distance upper bound constraints to achieve accurate localization estimates in obstructed environments. It uses the same approach as the Centroid technique [10] but applies the distance upper bound constraints to achieve further accuracy. Another interesting take is the work done by Young-Bae Kong et al. [2]. Their approach is to perform localization using the grid-based MLE method, and then perform error detection by using the Min-Max algorithm to overcome the large attenuation measurement errors of the obstructed interferences. Finally they use the compensated RSS measurements to correct the localization error.

Our proposed scheme differs from these in that it uses the fact that not all signals are affected by obstructions in the network. It improves upon the linear least square method by eliminating the effects of the obstructed beacon signals. It tries to combine the RSSI measurements that contribute to a high degree of agreement towards the final location estimate. This is achieved using spatial correlation of initial estimated sensor locations that are calculated using different combinations of a few out of all beacon signals in a trilateration process.

III. Motivation and Problem Statement

This work was motivated by experiences from deployment of a real-life WSN that was developed by the authors for monitoring the health of equipment in a power substation. The project, sponsored by EPRI, was initiated in 2006, which resulted in the deployment of a 122-node WSN known as *ParadiseNet* in a TVA-operated power substation in Kentucky [11]. The location site and an illustraion of a deployed wireless sensor node is depicted in Figure 1. The need for a self-localization scheme in this network arises due to several reasons. Firstly, it is extremely difficult to record and track the locations of sensor nodes in such large scale deployments, especially when nodes are sometimes displaced due to requirements imposed by monitoring tasks, network formation, and expansion. Secondly, several proposed energy coserving protocols and algorithts that are currently under development require the nodes to be aware of their locations. Such deployment sites can easily allow the movement of a robotic beacon transmitter that can be used for self-localization. While the technique is technically feasible, the main difficulty in using a beacon assisted localization scheme in such locations is that the presence of large objects (e.g. transformers, circuit breakers, metal boxes and beams, etc.) in the field can cause significant errors to the RSSI measurements due to shadowing. Hence, such a beacon assisted localization scheme would be accurate if the sensor nodes could automatically select the beacon signals that were relatively unaffected by shadowing effects.

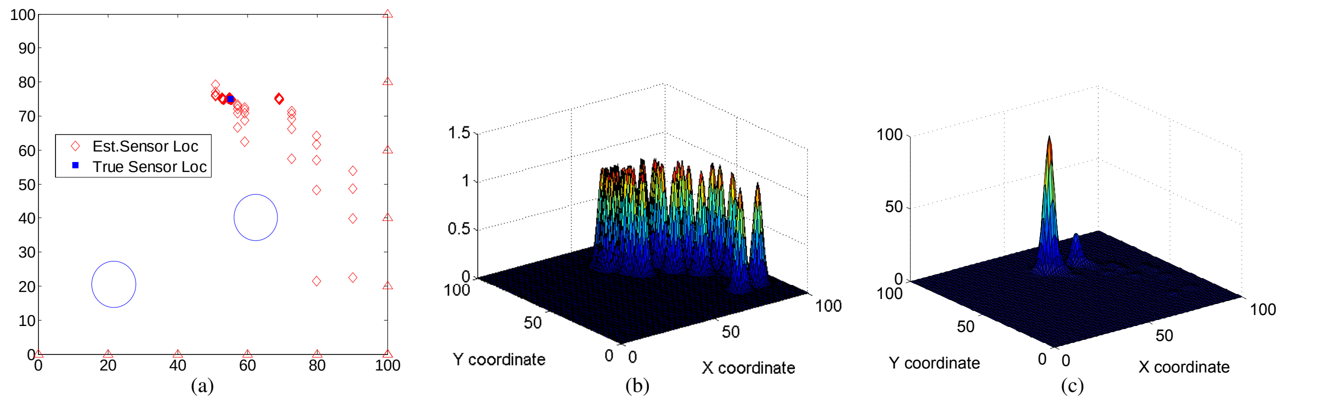


Fig. 2. Illustration of the proposed localization scheme from simulations: (a) Simulation topology showing obstructions in blue circles, anchor positions using triangles, and corresponding estimated locations from subsets of three beacons using diamonds; (b) bivariate Gaussian functions with mean centered at the estimated locations; and (c) addition of the Gaussian functions, showing the final location estimate.

The scenario described above is quite general and may be observed in other WSN deployments. Consequently, we pose the localization problem as follows. We assume that a set of wireless sensor nodes are randomly deployed in a given geographical area that is serviced by a set of B beacon generators to assist node localization. The beacon generators broadcast RF signals that include their locations, which are assumed to be known. A moving robot equipped with a GPS and RF hardware to transmit its locations periodically as it travels along a selected path in the deployment area is one approach for implementing such beacon generation. Sensor nodes apply RSSI measurements to estimate their distances from the beacons, by using a path loss model that is assumed to be known from offline channel measurements. Technically, a sensor node can compute its location estimate by using a minimum of three beacon signals that are transmitted from non-collinear locations and can apply multi-lateration to a larger set (potentially all) beacon signals received for improving this location estimate. The problem is to design a self-localization scheme for the sensor nodes that will use *a subset of the beacon signals received* to provide the highest accuracy of its location estimate from multilateration.

IV. Proposed Localization Scheme

The proposed scheme takes random subsets of M beacons ($M << B$) and performs multilateration to *each subset* to get a location estimate. This may involve a maximum of $\binom{B}{M}$ multi-laterations, which will result in as many location estimates for each node. The proposed scheme then applies *a clusterization technique* to select the most likely location that is in agreement with the maximum number of individual multi-laterations. The idea is that for subsets that include shadowed beacons, the estimated locations would be spatially uncorrelated. However, if a number of subsets of beacons are obtained from unobstructed beacons, they would have a high degree of spatial correlation. Consequently, combining the spatially correlated location estimates would eliminate the effect of shadowing, which cause large errors in location estimates. The concept is illustrated in Fig. 2 using a simulated scenario with 11 beacons located 20m apart on the x and y axes, and two circular obstacles. It is assumed that the RSSI of RF signals received from all beacons (red triangles on the axes) at the sensor node (blue rectangle) experience log-normal fading, whereas those obstructed by the two obstacles also experience shadowing. The results of triangulation from all combinations of subsets of 3 beacon signals at the sensor nodes are indicated by red diamonds. Spatial correlation of these triangulation results is obtained by superimposing a set of bivariade Gaussian distributions centered at each of these localization results (Fig. 2(b)), followed by addition (Fig. 2(c)). The final location estimate is obtained by taking the location of the peak of the summation.

A. Discussion of our algorithm

In this section we describe our localization scheme based on shadowing channel propagation model. As mentioned earlier, the unknown node first measures the RSSI received from the anchor nodes and estimate the distances from the corresponding anchors using a *channel model*. Then the position of the node is determined from these distances by using a multilateration algorithm and finally those estimates that areaffected by the obstacles are filtered. We model the radio channel propagation characteristic using the shadowing model where received power at a distance d is given by

$$P_r(d) = P_r(d_0) - 10.n.log\left(\frac{d}{d_0}\right) + X_\sigma \qquad (1)$$

where $P_r(d_0)$ is the received power at the reference distance d_0, n is the path loss exponent and X_σ is a zero-mean Gaussian random variable with standard deviation σ which comes from the channel noise and the shadowing effects. In our proposed scheme, the radio channel is modeled offline using a small set of RSSI measurements and parameters like n and $P_r(d_0)$ are fed into as the input of this scheme. Because of the spatio-temporal characteristics of the radio channel, in the estimated model these parameters may not be accurate representation of the real radio channel of an environment at any particular instance, which introduce some errors in the RSSI as well as distance estimation. Also in an obstructed environment the received power is highly disturbed due to the obstacles between the signal path of an anchor and the unknown node. Now we explain our proposed scheme that tries to reduce these disturbing effects in three stages as follows:

First stage: At first it forms all combinations of M non-collinear anchors that can be calculated from their positions sent in the beacon messages. Suppose there are N such non-collinear combinations. Also it stores the estimated distances calculated from all beacons from their corresponding RSSI measurements using the channel model described earlier with the estimated set of parameters fed into it.

Second stage: From each combination of M anchors (we use M = 3) formed in the first stage, we calculate a location estimate using multilateration (trilateration for M = 3) using linear least square method. This gives a total of N location estimates.

Here we discuss the linear least square method used to minimize the localization error. For an unknown node with position (x, y), the basic idea of localization is to

$$\text{Minimize } \varepsilon = |\sum_{i=1}^{M} \sqrt{(x_i - x)^2 + (y_i - y)^2} - d_i^2| \tag{2}$$

where d_i is the distance from the unknown node to the i-th anchor that is measured from the RSSI from the corresponding anchor. Note that the square of the distance between the unknown node and anchor node i can be expressed as

$$\begin{aligned}
&(x_i - x)^2 + (y_i - y)^2 = d_i^2 \ \forall i = 1, ..., M \\
&\Longrightarrow (x_i - x)^2 - (x_1 - x)^2 + (y_i - y)^2 - (y_1 - y)^2 \\
&\quad = d_i^2 - d_1^2 \ \forall i = 2, ..., M \\
&\Longrightarrow 2x(x_1 - x_i) + 2y(y_1 - y_i) \\
&\quad = (d_1^2 - d_i^2) - (x_1^2 - x_i^2) - (y_1^2 - y_i^2) \\
&\qquad \forall i = 2, ..., M
\end{aligned} \tag{3}$$

Expressing equation (3) in matrix form we get

$$\begin{bmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) \\ \vdots & \vdots \\ 2(x_1 - x_M) & 2(y_1 - y_M) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_M \end{bmatrix} \tag{4}$$

In the case of RSSI based localization, the real distances d_i between the unknown node and anchor node i is disturbed by channel noise, obstacles and other shadowing effects. Because of these effects, instead of having a real distance d_i, we get some noisy estimations $\tilde{d_i}$. Therefore, the system of equation can be written as

$$A.\bar{x} = \tilde{b} \tag{5}$$

where $A = \begin{bmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) \\ \vdots & \vdots \\ 2(x_1 - x_M) & 2(y_1 - y_M) \end{bmatrix}$, $\bar{x} = \begin{bmatrix} x \\ y \end{bmatrix}$ and $\tilde{b}$ is given by

$$\begin{bmatrix} \tilde{b_1} \\ \vdots \\ \tilde{b_M} \end{bmatrix} = \begin{bmatrix} (\tilde{d_1^2} - \tilde{d_i^2}) - (x_1^2 - x_i^2) - (y_1^2 - y_i^2) \\ \vdots \\ (\tilde{d_1^2} - \tilde{d_i^M}) - (x_1^2 - x_i^M) - (y_1^2 - y_i^M) \end{bmatrix} \tag{6}$$

Therefore, the position of the unknown node can be calculated by minimizing $\|A.\bar{x} - \tilde{b}\|^2$. By using the least-squares method we get the solution of this equation as $\hat{x} = (A^T A)^{-1} A^T \tilde{b}$.

Third stage: As mentioned earlier, due to the radio channel characteristics and obstacles, the unknown node receives a disturbed RSSI measurements and distance estimate. This stage distinguishes whether or not an estimate is affected by obstacles among these N estimates by looking at their spatial distributions in the field of operation. We assume that the position estimates are $\{x_i, y_i\}$ $\forall$ $i \in (i, ...N)$. Next we construct N bivariate Gaussian pdfs with the mean centered at $\{x_i, y_i\}$ $\forall$ $i \in (i, ...N)$ and superimpose them. This superposition of all pdfs give a Gaussian mixture density where the position estimates affected by obstructed beacon signals remain as outliers as far as the number of obstructed beacon signals are not very high. Then the (x, y) position of the peak point of this Gaussian mixture density is assumed as the final location estimation of the unknown node. Thus this process basically filters out the affected RSSI measurements in the presence of limited number of obstructions.

B. Optimization

Since a Gaussian function requires exponentiation, we replace it with a simpler function that comprises two concentric cylinders with radii r and $2r$. The first cylinder with radius r gets a height of α and the second cylinder gets a lesser height of β. This idea of two concentric cylinders is the approximation of the Gaussian pdfs. Then the same process of summing up of all the heights is applied and the position of the peak is chosen as the position of the unknown node.

The purpose of choosing $M = 3$ is mainly twofold. First, it reduces the computational complexity of multilateration which is important especially for low-power sensor motes that have low processing capabilities. Second, choosing $M = 3$ gives large number of possible location estimates which helps in producing a good Gaussian mixture density.

V. Performance Evaluation

This section presents evaluation results of our proposed localization scheme using both simulations as well as initial experiments. For simulations, we use an environment as depicted in Fig 2(a). We use a log-normal shadowing model with a path loss exponent of 4 and the standard deviation (σ) of the shadowing random variable is assumed to be 3. The obstacles used in the simulations are of 5 meter radius and the transmit power of the beacons are 0 dBm.

Fig 3 shows the variation of the average localization error obtained using the proposed localization scheme and that obtained from multilateration using all beacon signals together

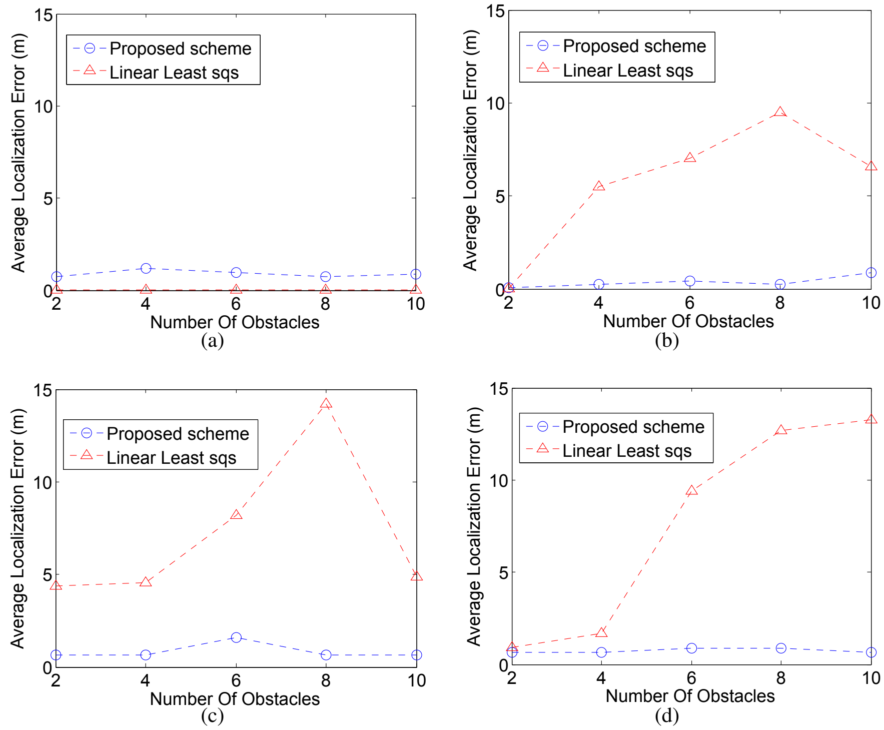


Fig. 3. Comparison of localization error of our proposed scheme with the linear least square method (a) $\sigma = 0$ (b) $\sigma = 3$ (c) $\sigma = 6$.

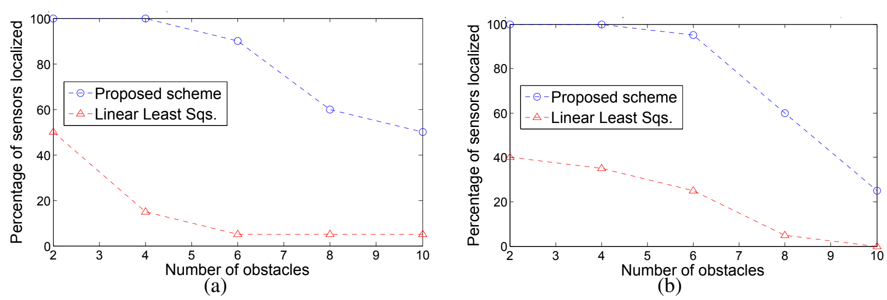


Fig. 4. Comparison of percentage of nodes localized of our proposed scheme with the linear least square method (a) $\sigma = 6$ (b) $\sigma = 9$.

(linear least square estimate) for varying number of obstacles [12]. It is observed that the proposed scheme reduces localization errors especially when there are obstacles in the network. Note that in an obstacle-free network, the proposed scheme has a higher error that the least square method. The reason is that the linear least squares method uses much more than three beacons signals (as used in the proposed scheme) to compute an unknown node locations. Fig 4 shows the percentage of nodes localized in two schemes which also shows an improvement in our scheme compared to the least square method.

Next we evaluate the effect of approximating the Gaussian function with the proposed concentric cylinders, which is shown in Fig 5. We make $\sigma = 6$ and $r = 3$ meters for this figure. From this figure we can observe that the average localization errors increase marginally while using concentric cylinders. Thus we conclude that our approximation performs very close

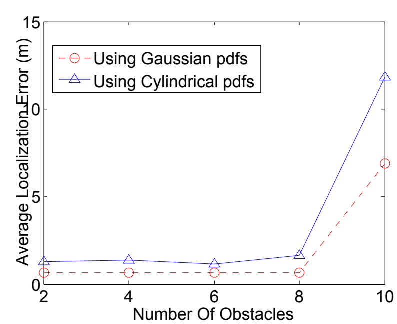


Fig. 5. Comparison of average localization errors using Gaussian pdfs and two concentric cylinders.

to the performance using Gaussian pdfs.

To show the performance of our proposed scheme in a real world scenario, we experiment with 11 MICAz anchors and

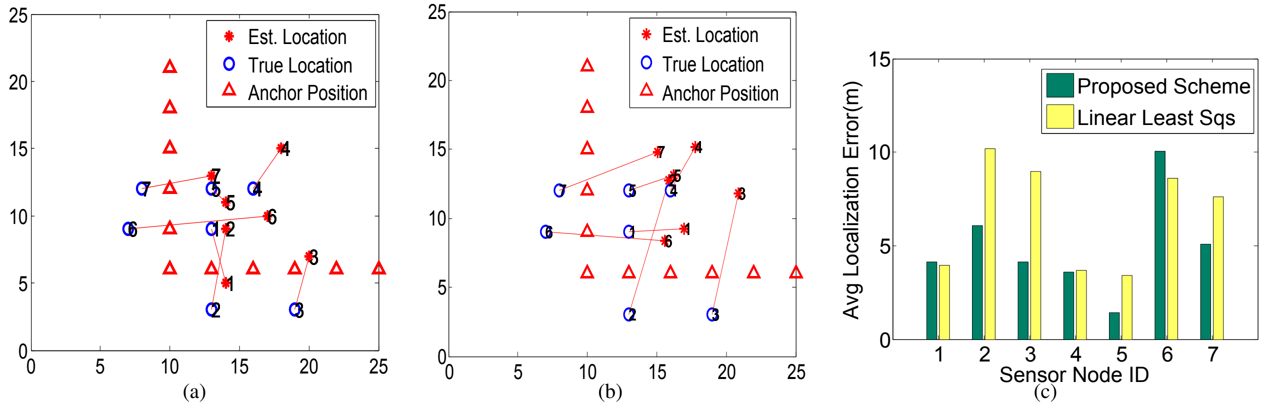


Fig. 6. (a) Experiment scenario where triangles are the positions of the anchors using our proposed scheme. (b) Using Linear Least Square Method. (c) Comparison of average localization error for each node of these two schemes.

7 MICAz unknown nodes in an area of 25 $\times$ 25 meter^2 as shown in Fig 6. The deployment location was one that comprises airconditioning equipment for campus buildings, which posed as obstructions in our work. Fig 6(c) shows the average localization errors for each unknown nodes in two schemes. From these figures we can observe that the errors are reasonable even if a challenged obstructed scenario which establishes the effectiveness of our proposed scheme. Also compared to the least mean square method, our proposed scheme gives lesser errors in most of the unknown sensor node positions.

VI. Conclusions and Future Works

This paper presents a simple and effective range-based self localization scheme that uses the peak of a bivariate Gaussian mixture to localize an unknown node in an obstructed sensor network environment. A key advantage of the scheme is that it is effective in negating the effects of erroneous distance calculations in node localization within an obstructed sensor network. The proposed scheme shows accuracy in localizing an unknown node in the presence of obstacles within a sensor network. In future, we intend to implement and test our proposed scheme in large real life monitoring environments.

Acknowledgement

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