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Optimum Sensor Node Localization in Wireless Sensor Networks

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***Abstract*: Scientists, engineers, and researchers use wireless sensor networks (WSN) for a wide array of applications. Many of these applications rely on knowledge of the precise position of each node. An optimum localization algorithm can be used for determining the position of nodes in a wireless sensor network. This paper provides an overview of different approach of node localization discovery in wireless sensor networks. The overview of the schemes proposed by different scholars for the improvement of localization in wireless sensor networks is also presented. Experiments were performed in a testbed area containing anchor and blind nodes deployed in it to characterize the pathloss exponent and to determine the localization error of the algorithm. Details regarding the implementation of new algorithm are also discussed in this paper.**

Keywords: **Optimum; Node localization; Sensor Networks; Anchor node; precise positioning.**

I. INTRODUCTION

Wireless sensor networks (WSN) consist of hundreds to thousands of low-power multifunctioning sensor nodes, operating in an unattended environment, with limited computational and sensing capabilities. Awareness of location of these nodes is one of the important and critical issue and challenge. It is an crucial requirements in designing of solutions for various issues related to WSN. Being used in environmental applications to perform the number of task such as environment monitoring, disaster relief, target tracking, defences and many more, node localization is inherently one of the system parameters.

In order to take advantage of these of wireless sensor nodes, we need to account for certain constraints associated with them. Since the sensor nodes are equipped with small, often irreplaceable, batteries with limited power capacity, it is essential that the network be energy efficient in order to maximize the life span of the network [7, 8]. Conventional techniques such as direct transmissions from any specified node to a distant base station have to be avoided. Although Clustering and generating a sink node can be benificial but if the exact location of destination node is known, the transmitted energy can be estimated well in advance and thus lifetime of sensor can be predicted. Thus we can say that sensor node localization plays a very important role in any energy efficient algorithm at both inter-cluster and intra-cluster levels.

II. RELATED WORK

The introduction of mobile sinks in WSN s has gained more and more attention to balance energy consumption and prolong network lifetime. In 2005 and 2006, some predefined sink movement traj ectories were studied. In [5],the authors investigated the benefits of a heterogeneous architecture for WSN s composed of a few resource-rich mobile nodes and a large number of simple static nodes. They studied WSN s with one mobile sink and one mobile relay individually. In [6], the authors studied a base station which moves along a predetermined movement path to collect data from cluster heads

(CHs). Sensor nodes which were closest to mobile sink trajectory will be chosen as CHs, and CHs sent data to mobile node as it passed by.

But how will a sensor node keep track of the neighboring nodes? The answer is localization. Localization in sensor networks can be defined as identification of sensor node's position for any WSN, the accuracy of its localization technique is highly desired but the main problem we face in attaining it is locating the geometrical position of the sensor node in the network. Localization problem is an estimation of position of wireless sensor nodes and to coordinate with one another. Localization is a challenge which deals with wireless sensor nodes and it has been studied from many years. There are different solutions and they are evaluated according to cost, size and power consumption.

Localization is important when there is an uncertainty of the exact location of some fixed or mobile devices. One example has been in the supervision of humidity and temperature in forests and/or fields, where thousands of sensors are deployed by a plane, giving the operator little or no possibility to influence the precise location of each node.[9,10]. Therefore, the network localization problem, namely, the problem of determining the positions of nodes in a network, has attraction of many engineering field and have been researched for many years. The device whose location is to be estimated is called localization node, and the network entity with known location is called localization base station.

III. LOCALIZATION TECHNIQUES

Wireless sensor network consists of a large set of inexpensive sensor nodes with limited processing and computing resources. Thus, algorithms designed for wireless sensor networks need to be both memory and energy efficient. In most of the algorithms for wireless sensor network, it is assumed that the sensor nodes are aware of their locations and also about the locations of their nearby neighbors. Hence, localization is a major research area in wireless sensor networks. Nodes can utilize a global positioning system, but this solution is typically verycostly. Many researchers are focusing on designing different algorithm but paying less attention on range measurement inaccuracy Localization is usually carried out by measuring certain distance dependent parameters of wireless radio link between the localization node and different localization base stations.

Existing location discovery approaches basically consists of two basic phases:

(1) Distance (or angle) estimation

(2) Distance (or angle) combining

The most popular methods for estimating the distance between two nodes are described below:

Received Signal Strength Indicator (RSSI): RSSI measures the power of the signal at the receiver and based on the known transmit power, the effective propagation loss can be calculated. Next by using theoretical and empirical models we can translate this loss into a distance estimate. This method has been used mainly for RF signals. RSSI is a relatively cheap solution without any extra devices, as all sensor nodes are likely to have radios. The performance, however, is not as good as other ranging techniques due to the multipath propagation of radio signals.

Time based methods (ToA, TDoA): These methods record the time-of-arrival (ToA) or time-difference-of-arrival (TDoA). The propagation time can be directly translated into distance, based on the known signal propagation speed. These methods can be applied to many different signals, such as RF, acoustic, infrared and ultrasound. TDoA methods are impressively accurate under line-of-sight conditions. But this line-of-sight condition is difficult to meet in some environments. Furthermore, the speed of sound in air varies with air temperature and humidity, which introduce inaccuracy into distance estimation. Acoustic signals also show multi-path propagation effects that may impact the accuracy of signal detection.

Angle-of-Arrival (AoA): AoA estimates the angle at which signals are received and use simple geometric relationships to calculate node positions. Generally, AoA techniques provide more accurate localization result than RSSI based techniques but the cost of hardware of very high in AoA.

For the combining phase, the most popular alternatives are:

Hyperbolic trilateration: The most basic and intuitive method is called hyperbolic trilateration. It locates a node by calculating the intersection of 3 circles as shown in Fig. 1(a).

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Triangulation: This method is used when the direction of the node instead of the distance is estimated, as in AoA systems. The node positions are calculated in this case by using the trigonometry laws of sines and cosines (shown in Fig. 1(b)).

Maximum Likelihood (ML) estimation: ML estimation estimates the position of a node by minimizing the differences between the measured distances and estimated distances (shown in Fig. 1(c)).

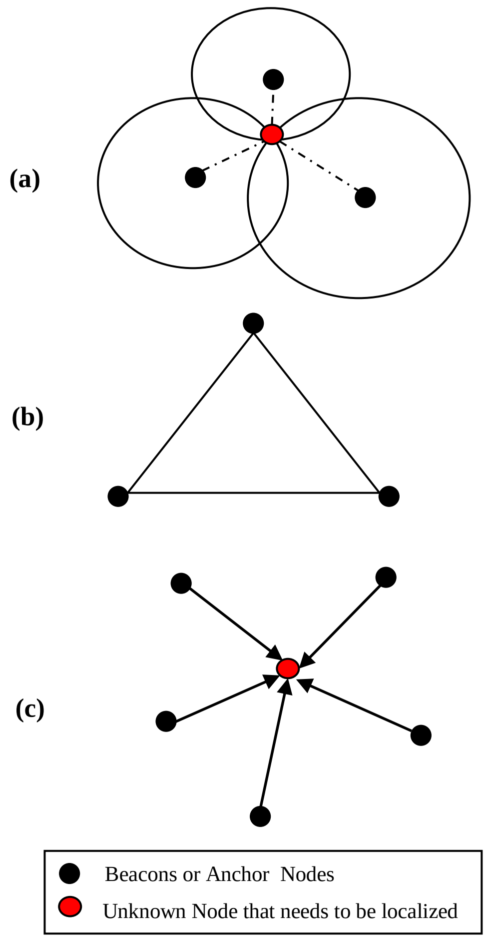

Fig. 1: Localization techniques (a) hyperbolic trilateration (b) Triangulation (c) Maximum Likelihood Estimation

IV. RELATED WORK

Consider the case when we have deployed a sensor network consist of N sensors at locations S = {S_1, S_2,…….,S_N}. Let S_x^i refer to the x-coordinate of the location of sensor i and let S_y^i and S_z^i refer to the y and z coordinates, respectively. Constraining S_z^i to be 0 suffices the 2D version of this problem. Determining these locations constitutes the localization problem. Some sensor nodes are aware of their own positions; these nodes are known as anchors or beacons. All the other nodes localize themselves with the help of location references received from the anchors. So, mathematically the localization problem can be formulated as follows: given a multihop network, represented by a graph G = (V, E), and a set of beacon nodes B, their positions {x_b, y_b} for all b ε B, we want to find the position {x_u, y_u} for all unknown nodes u εU.

In this section, we present a probabilistic position estima-tion algorithm that considers range measurement inaccuracies. Nodes in a sensor network can belong to two different classes, namely beacons and unknowns. We assume that the beacons have known positions (either by being placed at known posi-tions or by using GPS), while the unknown nodes estimate their position with the help of beacons. The first step in RF-based localization is range measurement, i.e estimating the distance between two nodes, given the signal strength received by one node from the other. RF-based

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signal strength measurements are usually prone to inaccuracies and errors and, hence, calibration of such measurements is inevitable before using them for localization. For this algorithm to work, extensive preliminary field measurements and calibrations were carried out as discussed in the following subsections.

At a high level, the guidelines are a result of the fact that the probability ofextremely high location error results from anchor nodes being roughly in a geograph-ically straight line. As the anchor nodes are spread out from a straight line, the probability of high errors decreases, leaving network designers a relatively simple chore when choosing anchor nodes locations.

a. Basic Framework:

As far as empirical evidence is concerned, authors will come across anchor placement by accident and discuss it basedon their own empirical evidence. Shang, et al. [2] and Li, et al. [3] both choose anchors at random within the network. Although, Shang, et al., do mention that a co-linear set of anchors chosen in one example ”represents a rather unlucky selection”, without supporting evidence of why this is unlucky. Earlier work by Doherty, et al. [1] requires anchor nodes to be placed at the edges, and ideally at the corners of the network. In this case, however, the algorithm is a simple constraint problem. One constraint requires that all the unknown nodes be placed within the convex hull of the anchors, and therefore, better results are obtained when anchors are at the corners.

An undirected topology of the sensor networks is described by the tuple T = (N; E; W), where N, E and W represent the set of sensor nodes, edges connecting pair of nodes and weights assigned to edges between each pair of nodes respectively. Weights in this context refer to the received signal observations assuming one node is transmitting and other is receiving. The weight is invariant in both direction i.e. $\{w_{ij} = w_{ji}\}$ ε R. The location of sources are assumed to be known. Location of the ith source is represented by $(\alpha^i, \beta^i, \gamma^i)$, 2 S , wherei εS is the set of source nodes. (x^i_t; y^i_t; z^i_t), i ε N denotes the location of unknown ith mobile node at each instant t. The problem of localization is to find the location of these mobile nodes at each instant. To estimate the location of mobile nodes, distances from each of the sources are computed.

The distance between pair of nodes is estimated based on received signal strength [12, 13] and shown below.

$$Pt - Pr = 10n_e \log d - 10\log(Gt\,Gr\left(\frac{\lambda}{4\pi}\right)n^e) + X\sigma \quad (1)$$

Where, Pt and Pr are the transmitted and received signal powers in dB respectively. d, n_e and $X\sigma$ denote the distance between pair of nodes, path loss exponent and noise respectively. Gt, Gr and λ are the transmitting antenna gain, receiving antenna gain and carrier wavelength respectively. In the following Section, relationship between received signal and distance is established experimentally for different modalities of signal.

b. Major sources of Error and Calibration

AOA measurements are impaired by the same sources discussed in the TOA section: additive noise and multipath. The resulting AOA measurements are typically modeled as Gaussian, with ensemble mean equal to the true angle to the source and stan-dard deviation σα. Theoretical results for acoustic-based AOA estimation show standard deviation bounds on the order of $\sigma_\alpha=2^\circ$ to $\sigma_\alpha=6^\circ$, depending on range [49]. Estimation errors for RF AOA on the order of $\sigma_\alpha=3^\circ$ have been reported using the RSS ratio method [14].

It is not likely that sensors will be placed with known orienta-tion. When sensor nodes have directionality, the network local-ization problem must be extended to consider each sensor’s orientation as an unknown parameter to be estimated along with position. In this case, the unknown vector θ is augmented to include the orientation of each sensor. The models presented earlier are sufficient to find bounds on localization performance in cooperative localization. These lower bounds are not a function of the particular localization algorithm employed. Thus we have presented some of these performance limitions in this section before discussing algorithm of this research.

In particular, each sensor estimates its coordinates by finding coordinates that minimize the total squared error between calculated distances and estimated distances.

Sensor j's calculated distance to seed i is:

$$d_{ji} = \sqrt{[}\,(x_i - x_j)^2 + (y_i - y_j)^2 \quad (2)$$

and sensor j's total error is:

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$$\mathrm{Ej} = \sum_{1}^{n}(\mathrm{dji} - \mathrm{d\hat{}ji})^2 \qquad (3)$$

In equation (2) and equation (3), n is the number of seed sensors and $d\hat{}_{ji}$ is the estimated distance computed through gradient propagation. The coordinates are then incrementally updated in proportion to the gradient of the total error with respect to that coordinate.

V. PROPOSED APPROACH

The goal of proposed algorithm is to determine specific blind node's location within the distributed nodes along the testbed area. If the positions of the blind nodes are not known in a network, the event these monitor and report can not be located if need be. The primary obstacles to localization in wireless sensor network is the sparse anchor node problem, hence, this algorithm is structured to solve the problem.

Features of required Algorithm:

- Interferomatric ranging based localization that takes error propagation into account.
- Attack the challenges of Information Asymmetry.
- Secure and robust.
- Accuracy.
- Incresed flexibility by taking obstacles into account.

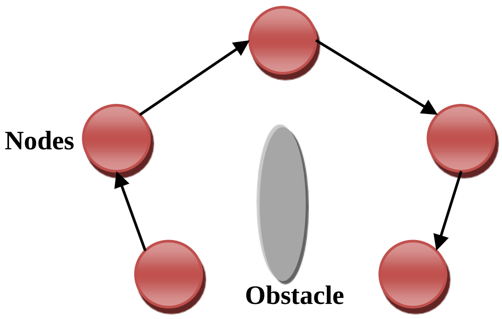

Fig. 2: Difference in hop count distance in the presence of an obstacle.

Consider Fig. 2 where the hop count distance between 1 and 5 node is four hops due to the obstacle, but the real distance is far lesser than four values. Thus it is important for algorithm to readjust itself in the presence of an obstacles. It requires substantial node density before its accuracy reaches an acceptable level as the shown hop count is not reliable in measurement because environmental obstacles can prevent edges from appearing in the connectivity graph that otherwise would be present as shown in Fig 2.

In this section, we present a probabilistic position estima-tion algorithm that considers range measurement inaccuracies. Nodes in a sensor network can belong to two different classes, namely beacons and unknowns. We assume that the beacons have known positions (either by being placed at known posi-tions or by using GPS), while the unknown nodes estimate their position with the help of beacons. The first step in RF-based localization is range measurement, i.e estimating the distance between two nodes, given the signal strength received by one node from the other. RF-based signal strength measurements are usually prone to inaccuracies and errors and, hence, calibration of such measurements is inevitable before using them for localization.

The proposed algorithm is made up of two phases: startup phase and the resultant phase.

a. Startup phase:

The first phase is a heuristic that produces a graph embedding which looks similar to the original embedding. The authors assume that each node has a unique identifier and the identifier of node i is denoted by ID_i and the hop-count between nodes i ad j is the number of nodes $h_{i,j}$ along the shortest path between i and j. The algorithm first elects the five reference nodes in which four nodes n1, n2, n3 and n4 are selected such that they are on the periphery of the graph and the pair (n1, n2) is roughly perpendicular to the pair (n3, n4). The node n5 is elected such that it is in the middle of the graph. At first the node with smallest ID is selected.

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Next the reference node n1 is selected to maximize $h_{1,2}$. After that n3 is selected to minimize $|h_{1,3}- h_{2,3}|$ and the tie-breaking rule is to pick the node that minimizes $h_{1,3}+ h_{2,3}$. In the next stage n4 is selected to minimize $|h_{1,4}- h_{2,4}|$ and the ties are broken by picking the node that maximizes $h_{3,4}$. Now for all nodes ni the heuristics uses the hop-counts h1,i, h2,i, h3,i, h4,i, and h5,I from the chosen reference nodes to approximate the polar coordinates (ρi, θi) where:

$$\rho i = h5, i * R \qquad (4)$$

$$\theta i = \tan^{-1}[(h1, i - h2, i) / (h3, i - h4, i)] \qquad (5)$$

b. Resultant phase:

In the second phase, each node n_i calculates the estimated distance $d\hat{}_{i,j}$ to each neighbours nj and it also knows the measured distance $r_{i,j}$ to neighbour n_j. Now if $v\hat{}_{i,j}$ represent the unit vector in the direction from $p\hat{}_i$ to $p\hat{}_j$ ($p\hat{}_i$ and $p\hat{}_j$ at the current estimates of i and j respectively) then the force $F_{i,j}$ in the direction $v\hat{}_{i,j}$ is given by:

$$Fi,j = v\hat{}i,j \; (d\hat{}_{i,j} - r_{i,j}) \qquad (6)$$

And the resultant force on node i is given by

$$F_i = \sum i,,j \; F_{i,j} \qquad (7)$$

The energy Ei,j of nodes ni and nj due to the difference in measured and estimated distances is the sequence of the magnitude of Fi,j and the total energy of node i is equal to:

$$E_i = \sum_j E_{i,j} = \sum_j (d\hat{}i, j - ri, j)^2 \qquad (8)$$

And the total energy of the system E is given by:

$$E = \sum_i Ei \qquad (9)$$

Now the energy Ei of each node ni reduces when it moves by an infinitesimal amount in the direction of force Fi. In the optimization, the magnitude of Fi for each node ni is zero and the global energy of the system E is also zero and the algorithm converges.

VI. SIMULATION RESULTS AND ANALYSIS

To study the robustness of the proposed localization algorithm, a MATLAB program was developed; this program implemented the algorithm using the input statement and other matlab statements which is more interactive and better for analysis.

a. Data Collection

The Table1 is based on the existing experiments which uses a different randomly-generated topology and a Zigbee CC2420 Module.

Table 1: Total Average Receive Signal Strength w.r.t distance

Distance (m)	RSSI (dBm)
1	-44.8
2	-47.7
3	-48.7
4	-53.1
5	-55.6
6	-61.8
7	-67.2
8	-66.5
9	-69.0
10	-67.3

From Table 1 the data collected was used to develop a graph and for computing the pathloss exponent n of the testbed area using eq. (1). From the computation, as shown in fig. 3 was computed to be 2.2. Hence, n = 2.2 will be used as the pathloss exponent in this research work.

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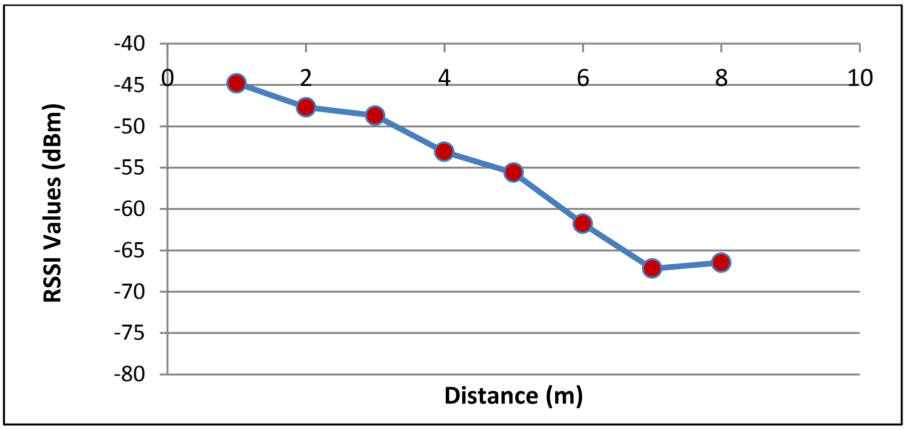

Fig. 3: The average values of RSSI obtained vs. distance

b. Processing collected Data

As per an experiment [15] they measured the signal strength and noise in intervals of 2.5m up to 50m. For each distance, we measured the data at 16 different positions. It was noted that a significant change in signal strength as a function of distance, while the noise remained almost the same; so, we considered only the signal strength information in our analysis.

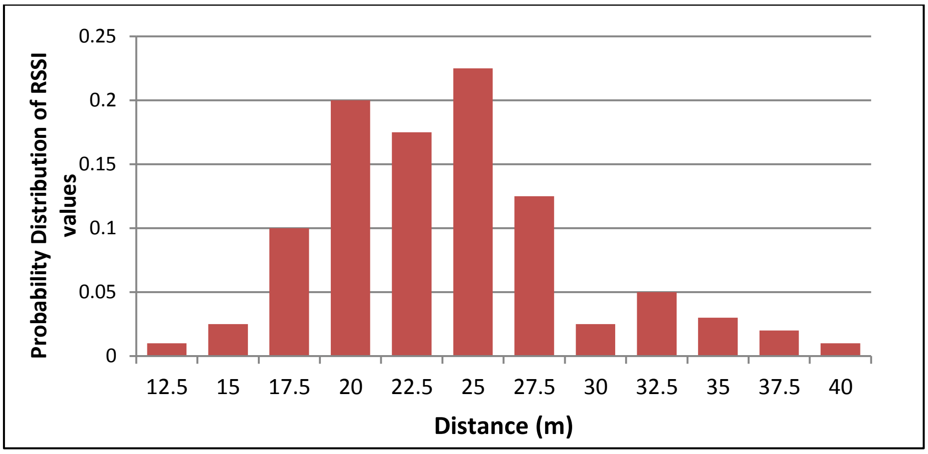

Fig. 4: Probability distribution of signal strength with distance

Fig. 4 shows a graph with a normal fit for data collected with a received signal strength obtained by Zigbee module used. Themean and standard deviation for each signal strength was noted and tabulated as a function of distance.

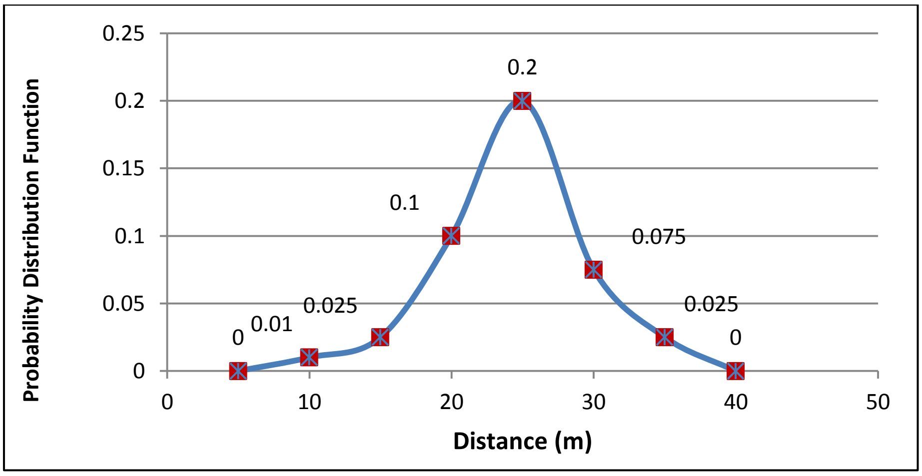

Fig. 5: Distribution of distances for a received signals and obtained RSSI

A graphical view of the table is shown in Fig. 5 for signal strengths ranging from 66 to 90. As per our proposed algorithm, the method uses this table for ranging; i.e., any node receiving a beacon packet will estimate itself to be located on a surface that has a probability distribution dictated by themean and standard deviation corresponding to the signal strength received. Note that the bound on standard deviation of local-ization error is proportional to $(1/\gamma)^{1/2}$. It makes sense that the localization error is proportional to σ_T for TOA and σ_α for AOA.

c. Probabilistic Localization

Fig. 6. Shows results when only the distance based localization of a single target is considered. There can N anchor nodes in the system and one mobile node, we use the measured distances and we find the error in location of the mobile node using eq. (3).

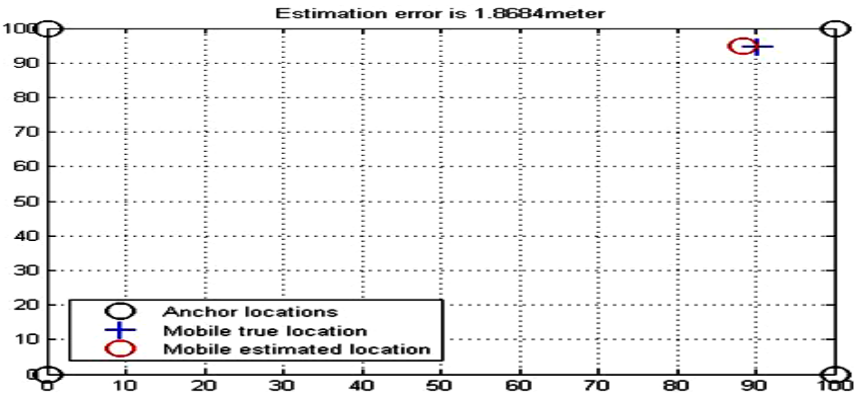

Fig. 6: Implementing localization using 4 anchor and 1 mobile user to find detection error.

Initial Parameters:

N = 4 (number of anchors)

M = 1 (number of mobile nodes)

NoisePow = 20;

The estimated error w.r.t to correct postion of anchor is found out to be 1.8668m when we have considered a 100mX100m plot. It means that the accuracy of distance measurement is 90 % for instance the inaccuracy of a 1m measured distance is around 0.1 meter. Thus Impliementing c. Probabilistic localization concept for self optimization of sensor node is acheived.

d. Implementing Localization on a randomly deployed wireless network

The first hypothesis was to choose nodes as anchors that we expect to have high location accuracy. Because we are trying to provide an a priori design technique for network planners, the information chosen to reach this goal must be applied to the randomly deployed network, as shown in Fig. 7. With this implementation we found that on an average, increased network density results in higher localization accuracy [2, 16]. Since the range-free algorithms depend heavily on network connectivity, the theory is that nodes with more neighbors will have lower location errors. The lower error in the anchors themselves should then translate into a more accurate transformation of the entire network.

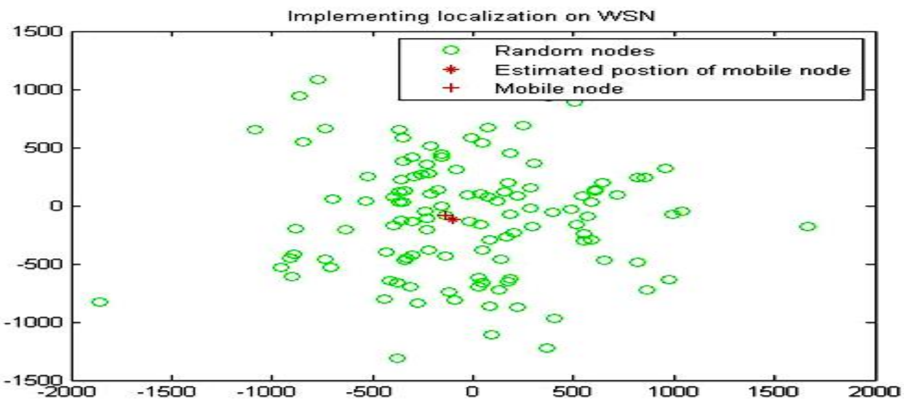

Fig. 7: The sample WSN used for showing localization of randomly selected mobile node.

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A simulator can be very useful in geographic routing application of sensor localization where the use of the coordinates of sensors can reduce routing tables and simplify routing algorithms. Localization errors, however, can adversely impact routing algorithms, leading to longer paths and delivery failures [18]. For the purposes of routing efficiency, actual geographical coordinates may be less useful than "virtual" coordinates [19] (i.e., a representation of a sensor's 'location' in the graph of network connectivity).

Researchers who are testing localization algorithms, like those presented in the later section on algorithms for location estimation, can use WSN localization simulators as well. These kind of softwares provide public access to a multifeatured MATLAB-based code and GUI for the calculation of the localization as shown in Fig. 8. It allows the inclusion of device orientation and clock biases as unknown nuisance parameters. Sensors can be arranged visually using the GUI and the bound can be calculated.

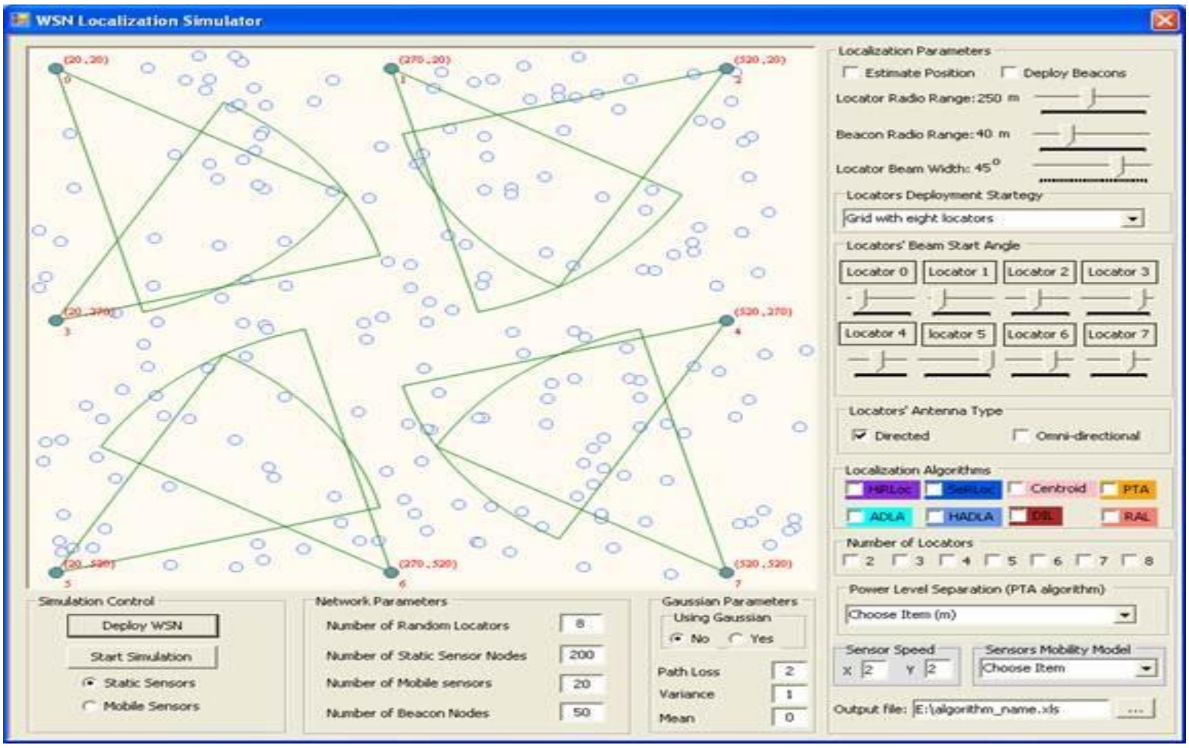

Fig. 8: Using WSN localization Simulator for deploying MATLAB program designed for single mobile node in multiple node environment

VII. CONCLUSION

Some localization schemes have fewer merits and greater demerits and some of them have less demerits and greater merits. These merits and demerits were the main source for proposing the idea of a unique approach which is the enhanced composite approach. In this paper, we have described a novel, robust and dis-tributed algorithm for localizing nodes in sensor networks. The approach is probability based and takes range measurement inaccuracies into account, which, according to our knowledge, have not yet been pursued in literature. Our Extensive outdoor field measurements and calibration indicate that a received signal strength is inaccurate and the proposed approach uses this information directly for ranging.

In this paper, we have described a novel, robust and dis-tributed algorithm for localizing nodes in sensor networks. Also, this algorithm accounts for the impact of wireless channel and variation of received signal observation with time and due to environmental conditions with the help of the volume constraints. The approach is RSSI based and takes range measurement inaccuracies into account, which, according to our knowledge, have not yet been pursued in literature. The proposed algorithm performs consistently well irrespective of the variation in the localization duration and radio communication range. Our focus of future work is on developing a three dimensional localization algorithm in mobile sensor networks using mobile nodes and anchors.

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