3-D Localization with Rb-Rf Methods for Noisy Distance Measurements & Scalability

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Abstract

Wireless sensor networks are dynamically formed over the varying topologies. Wireless sensor networks can assist in conducting the rescue operations and can provide search in timely manner. Long time monitoring applications are environment monitoring, security surveillance and habitat monitoring. Further, where it can be deployed in time critical situations when disaster happens. As we are dealing with the human lives here, we can't just rely on the localization schemes that depend upon the connectivity information Rf(range-free) algorithms only. Further, rescue operations are carried out in highly noisy environments, so distance based Rb(range-based) localization algorithms generate high error in distance measurements. An efficient algorithm is needed that can measure the location of the sensor nodes near to the living being or being attached to them in 3-D space with a high accuracy. To achieve such kind of accuracy a combination of both the strategies is required. The proposed method which incorporates both the Rb(range-based)&Rfrange-free strategies that successfully localizes nodes in a sensor network with noisy distance measurements. We also have depicted the effect of scalability on the performance of the algorithm. Results show that as the scalability of the network increases with the number of beacon nodes; the performance of the algorithm goes high above 90%. The granularity of the areas estimated may be easily adjusted by changing the system parameters which makes the proposed algorithm flexible.

Keywords: Wireless Sensor Network (WSN), Localization, Rf (Range free) & Rb (Range base)

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1. INTRODUCTION

Wireless sensor networks are dynamically formed over the varying topologies. Wireless sensor networks can assist in conducting the rescue operations and can provide search in timely manner. In general, disasters leave the situation worse without power and disruption of communication capabilities destroying the infrastructures [13]. A sensor network mainly consists of anchor nodes as well as the other nodes sensing the data. The anchor nodes are location aware sensor nodes which obtain its location information through some external methods (GPS, TOA [14, 15]). The un-localized nodes hear the beacons which are broadcasted by the anchor nodes. Determining the location of these un-localized sensor nodes with respect to the anchor nodes is called localization [12]. The localization algorithms generally possess wave-spreading like characteristics in which the intermediate sensor nodes become location aware and act as a new reference anchor node for the un-localized neighboring nodes. All the strategies that are employed for the localization in 2-D spaces are violated in 3-D spaces [1, 2]. 2-D spaces cannot be directly extended to 3-D just by increasing one parameter. For example, the 2-D localization completely fails in determining the depth of the river bed and other similar sensor network scenarios where the height comes into play. There are several well known problems that can be easily solved modeling the sensor network as 2-D but are very complex (sometimes NP-Hard) when modeled as 3-D [28-35]. Moreover, the main triangulation approach that is employed for the 2-D space doesn't fit for the 3-D The information received from the remote sensors that are several hops far is meaningless until and unless the location from where the data is received is known [13]. For large scale application scenarios where the geographical data is to be known for coarse parameters such as the temperature of an area, the data is aggregated for all the sensor nodes that are located nearby. Further, the location information is important for many location aware sensor network protocols. The positional information is used to partition the network into several clusters for hierarchical routing. For efficient routing the protocols require the information of the location of the sensor nodes.

The sensors employed near the disaster affected sites might contain the vital parameters of the living being trapped beneath several layers of collapsed surfaces. Based on the size of the area affected by catastrophe the data can be directed to the rescue team in a multi-hop way. The data so received by the rescue team can be processed and a map can be generated displaying the optimized path to send the help service in minimum possible time. Sensors can be deployed for continuous monitoring of some events that occur in physical environments, but we need a system that can act when some disaster occurs [16-20]. In disaster prone situations like earthquake and avalanche, the person is trapped beneath the various surfaces like collapsed buildings, snow masses, landslides, etc. To rescue the survivors, the information of location is crucial within short span of time.The contributions of the work presented in this paper can be shortly listed as follows.

- Calculation of the 3-dimentional location of sensors attached to the trapped persons lying beneath the several layers of overlapped surfaces relative to the beacon nodes deployed at the surfaces by the rescue team.
- Algorithm should be distributed so as to run on each sensor node.
- Propagation of location information from beacon nodes to the bottom surface passing through several layers of sensors as the radio range of beacon nodes extend only up to the sensors of the neighboring layers.

The rest of the this paper is organized as follows:Section II gives a survey of the related works.Section III presents the derivation of the proposed algorithm and work approach towards the solution of the problem.Section IV shows all the comparative simulations results along with the output figure .

2. Related Work

In this section ,we review research most relevant to our work . The wireless sensor network is an open research field. All the components of this network are still in developing phase. Many different localization algorithms have been proposed until now. As the sensor networks are application specific it is quite hard to generalize the algorithm approaches for localizations that suits to all the different scenarios [21-27].

All the localization algorithms have been broadly classified into two major categories: Rb(range based) and Rf(range free). Both the strategies employ totally different way of approaches.

The Rb method relies on the distance measurements through different received signal strength strategies. Whereas, the Rf method relies on the connectivity information only i.e. the nodes can listen to the beacon from the sensor nodes. The wireless sensor network consists of localized anchor nodes and un-localized sensor nodes. The Rf(range free) method uses the connectivity information and bound the nodes location to the common overlapped (intersected) area. Different algorithms use different methods to calculate the nodes location information within the bounded region with respect to the anchor nodes. The range-based method uses the sophisticated hardware, radio signals to estimate the distance between the receiver and the transmitter antennas. Moreover, the range-free approach reuses the wireless communication radio signals to determine the connectivity between neighboring sensors and requires no extra hardware support. The range-free methods are used where the precise location of the sensor nodes is not required and the coarse position estimation up to some level is tolerable.

A. Range-Based Localization Schemes

Received Signal Strength (RSS): RSS is defined as the power measured by a received signal strength indicator (RSSI) by the receiver. Often, RSS is equivalently reported as measured power, i.e., the squared magnitude of the radio signal strength. We can consider the RSS of low frequency, RF, or other signals. Wireless sensors nodes communicate with neighboring sensors, so the signal strength of the radio can be calculated by each receiver during normal data communication without requiring additional bandwidth or energy requirements. RSS measurements are relatively can be easily embedded in the motes, thought of their expensiveness they are most generally used method for distance calculation [6]. 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 [9]. TDoA [3] methods are impressively [2] 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. They rely on complex hardware that is expensive and energy consuming; making it less suitable for sensor networks where the scalability is high of the lifetime of the network is expected to be more [1].

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. By providing information about the direction to neighboring sensors nodes rather than the distance to adjacent sensors nodes, AOA measurements provide localization information complementary to the TOA and RSS [4] measurements. Sophisticated direction aware antennas with high synchronization clocks are need in this method . Similar to AOA, TOA and TDOA estimates require additional hardware too expensive to be used in high [5] scalable sensor networks.

B. Range-Free Localization Schemes:

Centroid Algorithm: Anchors send their location information to neighbors that keep an account of all received beacons. Using the averaged out information, simple centroid model is applied for estimation the listening nodes location. This protocol is referred as the Centroid algorithm. The following are the steps of the localization:

- Beacon node broadcasts their position.
- Sensor node listens for beacons from anchors nodes and if they are able to hear the beacons this means they are under the ranging area covered by these anchor nodes.
- Sensor node computes its position by averaging out all the beacon node locations.

this means they are under the ranging area coverd by these anchor nodes.

Sensor node computes its position by averaging out all the beacon node locations. In a range-free, proximity-based, a localization algorithm is proposed containing location information (x_i, y_i) that uses anchor beacons, to estimate sensor node position. After receiving these beacons from anchor nodes, a sensor node estimates its location using the following formula for 2-D space :

$$(x_{est,}y_{est}) = \left(\frac{x_1 + ... + x_N}{N}, \frac{y_1 + ... + y_N}{N} \right)$$

For 3-D space it can be further extended to:

$$(x_{est,}y_{est}, z_{est}) = \left(\frac{x_1 + ... + x_N}{N}, \frac{y_1 + ... + y_N}{N}, \frac{z_1 + ... + z_N}{N} \right)$$

The advantage of this Centroid localization scheme is its simplicity of calculation and simplicity in implementing it Figure 1.

DV-HOP:

DV-HOP assumes that a network consisting of identical sensing nodes and beacon nodes [7]. Instead of going for the single hop broadcast, anchors flood their locations all over the sensor network. As the information propagates over each hop an increment counter each time increments the hop count value [8]. Senor nodes calculate their position based on the received beacon locations, average distance per hop, the hop count from the corresponding anchor; the working of this strategy is quite similar to existing distance vector routing. One anchor node broadcasts a beacon to all over the network containing the beacon location with a hop count value initially set to one.

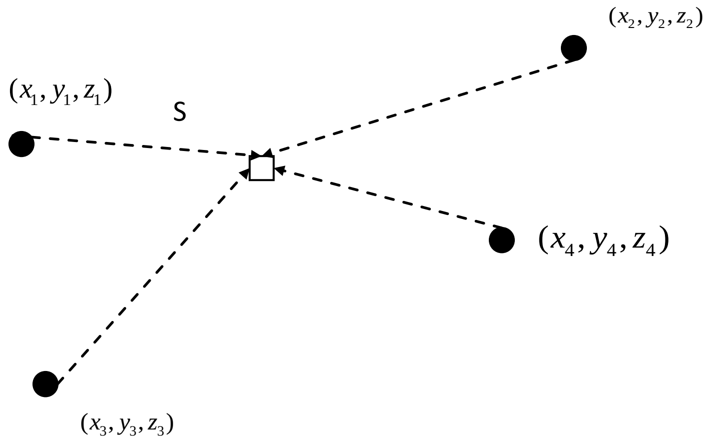

Figure 1: Centroid estimation

Multi-Dimensional Scaling (Mds): The multi-dimensional scaling is another type of range-free method. In a large scale sensor networks, Multi-Dimensional Scaling (MDS) only uses the connectivity information. This process has three steps: Roughly estimate the distance between all the sensor node pairs. Apply the MDS to derive locations fitted [10] roughly to the estimated distances. Optimize by taking the known sensor node locations.

SeRLoc :
SeRLoc [11] is range-free area based localization. The sensor network is formed of two types of nodes: sensor nodes and locators acting as anchor nodes. Un-localized sensor nodes are mounted with omni directional antennas and the anchor nodes i.e. locators are equipped with directional sectored antennas. The locators are previously localized nodes aware of its location. In SeRLoc, a sensor node calculates it location by listening the information transmitted by the locators.

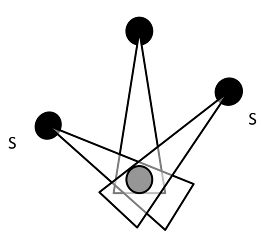

Figure 2: SeRloc, directional antennas, common intersection

3. PROPOSED 3D LOCALIZATION ALGORITHM

The following steps are performed for calculation of 3-D localization:

- The whole area is divided into grids. The interspacing between the grids is less than the range of the anchor nodes.
- A beacon node covers a block of cubes that are within its radio range. The cube size is such that it covers the largest area in the sphere formed by the radio range.
- The distance between the un-localized sensor node and the beacon nodes is calculated using different RSS techniques.
- A list is maintained by each un-localized node that contains the number of beacon nodes and the distance form each beacon node.
- The common cubical intersection areas of all the beacon nodes is found reducing the location possibilities.
- The common intersection area gives the bounded β values (max, min).The bounded values specifies the maximum and minimum values of co-ordinates. The nodes position should be within this rectangular region.
- Check whether the beacon nodes (≥3) are forming a plane i.e. they are not on same line.
- Calculate the location (x, y, z) of un-localized nodes taking the distances into account.
- Check the whether the calculated values within bounding region. All the values outside the region are discarded.
- Change the status of newly localized node to new beacon nodes for further calculation of other nodes.

C. The bounded area is explained below (Range-Free Approach):
Instead of considering a spherical area around a sensor node we consider the sensor node covers a

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cubical area. All the nodes within the cubical area can listen to anchor node other outside it are not considered to be covered by this anchor node [12].

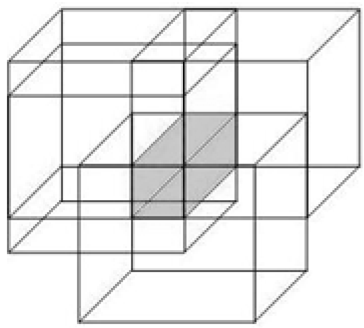

Figure 3: Intersection of bounding boxes, shaded region is the common bounded region

Each cube representing the [13] bounding area can be represented by the min & max values of its coordinates. The radio range covered by the beacon node P(x, y, z) varies between [$x$min , $y$min , $z$min] and [$x$max , $y$max , $z$max] represents the bounded range β of a node.

where, $$\begin{cases} x_{\min} = x - r + \partial \\ y_{\min} = y - r + \partial \\ z_{\min} = z - r + \partial \end{cases}$$

$$\begin{cases} x_{\max} = x + r - \partial \\ y_{\max} = y + r - \partial \\ z_{\max} = z + r - \partial \end{cases}$$

∂ corresponds to the error due to irregular radio pattern.

r average radio range of the beacon

$$[x_{\min}, y_{\min}, z_{\min}] \leq \beta \leq [x_{\max}, y_{\max}, z_{\max}]$$

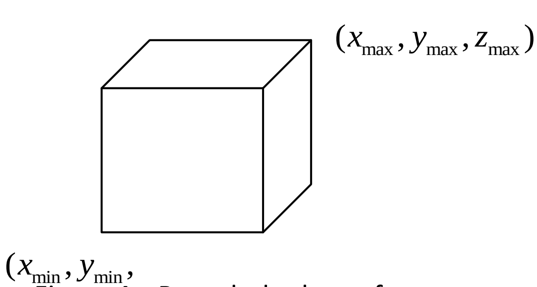

Figure 4 : Bounded values of sensor

The intersection of the two cubical areas [14] is done to reduce the area where the un-localized node is likely to be. As, more number of cubical areas [15] start to merge the common area of intersection starts to reduce. The new rectangular (sometimes square) area that emerges after multiple intersections of beacon nodes represents the bounded area.

For example intersection of two bounding cubes;

$$\beta_{new} = \beta_1 \cap \beta_2$$

$$[x_{new_{\min}}, y_{new_{\min}}, z_{new_{\min}}] \leq \beta_{new} \leq [x_{new_{\max}}, y_{new_{\max}},$$

Where $$\begin{cases} x_{new_{\min}} = |x_{2_{\min}} - x_{1_{\min}}| \\ y_{new_{\min}} = |y_{2_{\min}} - y_{1_{\min}}| \\ z_{new_{\min}} = |z_{2_{\min}} - z_{1_{\min}}| \end{cases}$$

$$\begin{cases} x_{new_{\max}} = |x_{2_{\max}} - x_{1_{\max}}| \\ y_{new_{\max}} = |y_{2_{\max}} - y_{1_{\max}}| \\ z_{new_{\max}} = |z_{2_{\max}} - z_{1_{\max}}| \end{cases}$$

Similarly, intersection of multiple boundaries can be done to lower the number of positions where a sensor node can be present.

$$\beta_{new} = \beta_1 \cap \beta_2 \cap \text{..........} \cap \beta_n$$

where, n is the number of beacon nodes covering a un-localized node

The method falls under the category of range-free as it only uses the connectivity information i.e. whether it is able to send & receive the beacon nodes from the respective beacon nodes.

D. Calculating from known distances (Range-Based):

The method uses the distance information [16] between the un-localized node and the beacon nodes. All the beacon nodes are considered to lie on same plane [17], w.r.t of these beacon nodes the nodes localization is determined. A set of three anchor nodes are selected at a time. These three anchor nodes form a equation of a plane.

The standard equation of a plane in 3 dimensional spaces is

Qx + Ry + Sz +D = 0

Here in equation (19), Q, R, S correspond to the anchor nodes & D corresponds to the sensor node with unknown location information

The normal to the plane is the vector (Q, R, S).

Given three points in space Q(x1, y1, z1), S(x2, y2, z2), S(x3, y3, z3) the equation of the plane through these points is given by the following determinants.

$$Q=\begin{pmatrix}1 & y_1 & z_1\\ 1 & y_2 & z_2\\ 1 & y_3 & z_3\end{pmatrix}\qquad \mathbf{R}=\begin{pmatrix}x_1 & 1 & z_1\\ x_2 & 1 & z_2\\ x_3 & 1 & z_3\end{pmatrix}$$

$$\mathbf{S}=\begin{pmatrix}x_1 & y_1 & 1\\ x_2 & y_2 & 1\\ x_3 & y_3 & 1\end{pmatrix}\qquad \mathbf{D}=-\begin{pmatrix}x_1 & y_1 & z_1\\ x_2 & y_2 & z_2\\ x_3 & y_3 & z_3\end{pmatrix}$$

Expanding the above gives :

$$Q=y_1(z_2-z_3)+y_2(z_3-z_1)+y_3(z_1-z_2)$$

$$\mathrm{R}=\mathrm{z}_1\ (\mathrm{x}_2-\mathrm{x}_3)+\mathrm{z}_2\ (\mathrm{x}_3-\mathrm{x}_1)+\mathrm{z}_3\ (\mathrm{x}_1-\mathrm{x}_2)$$

$$\mathrm{S}=\mathrm{x}_1\ (\mathrm{y}_2-\mathrm{y}_3)+\mathrm{x}_2\ (\mathrm{y}_3-\mathrm{y}_1)+\mathrm{x}_3\ (\mathrm{y}_1-\mathrm{y}_2)$$

$$\mathrm{D}=-[\mathrm{x}_1\ (\mathrm{y}_2\ \mathrm{z}_3-\mathrm{y}_3\ \mathrm{z}_2)+\mathrm{x}_2\ (\mathrm{y}_3\ \mathrm{z}_1-\mathrm{y}_1\ \mathrm{z}_3)+\mathrm{x}_3\ (\mathrm{y}_1\ \mathrm{z}_2-\mathrm{y}_2\ \mathrm{z}_1)]$$

The sign of, $\mathbf{s} = \mathbf{Qx} + \mathbf{Ry} + \mathbf{Sz} + \mathbf{D}$ determines which side the point (x,y,z) lies with respect to the plane. If s > 0 then the point lies on the same side as the normal (Q, R, S). If s < 0 then it lies on the opposite side, if s = 0 then the point (x,y,z) lies on the plane.

For a plane $Qx+Ry+Sz+D=0$ and a point $P(x_1,y_1,z_1)$ not necessarily lying on the plane, the shortest distance from P to the plane is :

$$\text{Distance} = \frac{|Qx_1+Ry_1+Sz_1+d|}{\sqrt{Q^2+P^2+S^2}}$$

It follows that if Distance = 0 in equation 24 then P lies in the same plane.

However, in real life environmental conditions where there is interferencing noise [18] the measuring and calculating errors might change [19] the distance a little bit. As a result P is considered lying within the same plane if it satisfies the constraint:

if $-\xi <$ Distance $< \xi$ then Distance ≈ 0

Where ξ is minute deviation caused due to errors.

p_i is the distance between the point P and the beacon nodes $B_i(|B_i|>3)$. The distances are measured by using different received signal strength (RSS) strategies. At least three beacon nodes are required to calculate the location of unknown sensor node. At first it is determined whether the nodes are forming a plane (Fig. 5).

$$(x-x_i)^2+(y-y_i)^2+(z-z_i)^2=p_i^{\,2}$$
$$i = 1, 2, 3\ldots$$

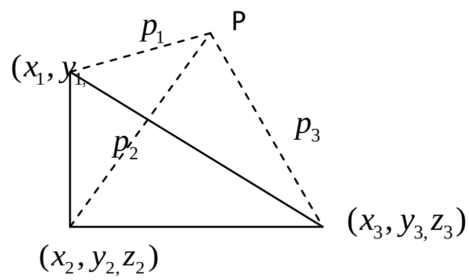

Figure 5: unknown coordinates of P; p_1, p_2, p_3

$$(x-x_1)^2+(y-y_1)^2+(z-z_1)^2-p_1^{\,2}=0$$
$$(x-x_2)^2+(y-y_2)^2+(z-z_2)^2-p_2^{\,2}=0$$
$$(x-x_3)^2+(y-y_3)^2+(z-z_3)^2-p_3^{\,2}=0$$

Solving, the above equations mathematically. For the variable z we get multiple values (as the root of the quadratic equations).By using the bounded cube (explained above) the proper values of x, y, z can be selected so, that it satisfies:

$$\beta=\beta_1\cap\beta_2\cap\beta_3$$

The β cube is calculated using the intersected cubical rectangle of beacon nodes.

$$P\in\beta$$

$$[x_{new_{\min}}, y_{new_{\min}}, z_{new_{\min}}]\le P[x,y,z]\le[x_{new_{\max}}, y_{new_{\max}}, z_{new_{\max}}]$$

Now substituting the values of z in other given equations we can derive values of (x,y,z). If an unknown node P receives signals from multiple anchor beacon sensor nodes. Then it will be decided first whether the beacon nodes are lying on the same plane or not. If they are not lying on the same plane then multiple beacon values giving rise to multiple equations are used for finding the values of p(x, y, z) & minimize the error:

$$(x-x_n)^2+(y-y_n)^2+(z-z_n)^2-d_n^2=0$$

Where, (x_n, y_n, z_n) correspond to the location of the beacon nodes

$$p=\begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

$$\alpha=\begin{bmatrix} 2(x_1-x_n) & 2(y_1-y_n) & 2(z_1-z_n) \\ 2(x_2-x_n) & 2(y_2-y_n) & 2(z_2-z_n) \\ \vdots & \vdots & \vdots \\ 2(x_{n-1}-x_n) & 2(y_{n-1}-y_n) & 2(z_{n-1}-z_n) \end{bmatrix}$$

$$k=\begin{bmatrix} (x_1^2+y_1^2+z_1^2)-(x_n^2+y_n^2+z_n^2)-(d_1^2-d_n^2) \\ (x_2^2+y_2^2+z_2^2)-(x_n^2+y_n^2+z_n^2)-(d_2^2-d_n^2) \\ \vdots \\ (x_{n-1}^2+y_{n-1}^2+z_{n-1}^2)-(x_n^2+y_n^2+z_n^2)-(d_{n-1}^2-d_n^2) \end{bmatrix}$$

Solving the above equations the approximated location can be calculated.

$$p=(\alpha^T\alpha)^{-1}\alpha^T k$$

Further, we bound the multiple values of x, y, z by selecting only those values which are within the bounding region and rejecting the ones which are outside it. The bounding region is where we have the constrained area of x, y, z.

$$\beta_{new}=\beta_1\cap\beta_2\cap...........\cap\beta_n$$

4. Simulation Results

The algorithm proposed here, as all the geometric approaches of the localization problem, requires a large number of sensor nodes and location aware beacons.MATLAB simulator is selected as it easily handles the matrix calculations very effectively & all the stress of the work can be given to the actual work rather than going on programming details.

We randomly generate the sensor node locations 3-D space that is constrained within the layer boundaries. However, the original beacon nodes are randomly distributed and constrained in 1st layer only.

$$x_i \in \{0, \text{max value of } x\text{-}y \text{ plane}\}$$

$$y_i \in \{0, \text{max value of } x\text{-}y \text{ plane}\}$$

$$z_i \in \{\, n\times d - \partial \ ,\ n\times d - \partial \,\}$$

where,

d - distance between the layers.

n - number of layer.

∂ - small deviation.

As the nodes in the network are randomly generated, some particularities can appear, such as isolated nodes or beacons in a corner. A sensor node on the edge of the cubical grid will hear half less beacons than another one in the centre, and thus this could decrease the overall efficiency. To get rid of such type of particular cases, every simulation is ran several times (6 to 10), and a mean value is taken out of the results. The simulation is performed by taking 1/3rd of the total nodes as beacon nodes. We have compared the parameters with a standard Center of Gravity (COG) method. The total time calculated here is the combined simulation time of both the proposed one and the COG method. Giving, an estimation of how much time this proposed algorithm will take to execute.

Performance Analysis:

The percentage of success of the algorithm proposed in this thesis is given by:

$$Per_{success}=100-\frac{\sum d_i}{N-n}*100$$

Where d_i – deviation between the actual location of nodes and the estimated location

N – total number of sensor nodes in the network (considering the first layer contains only beacon nodes).

n – number of nodes per layer

Error Analysis:

The error is calculated using:

$$d_{error}=\sqrt{(x_a-x_c)^2+(y_a-y_c)^2+(z_a-z_c)^2}$$

Where x_a, y_a, z_a - are actual sensor node location

x_c, y_c, z_c - are calculated sensor node location

Due to the many of involved parameters (number of nodes, communication range, number of anchor nodes, etc.) it's not feasible to make them all vary at the same time.

Effect of Scalability on the Performance:

Number of nodes	Anchor nodes	Communication Range (meter)	% Success in proposed	% Success in CO	Total time(sec)

			meth od	G met hod	
60	20	5	61.4	22.4	0.516 0
150	50	5	86.4	37.1	1.281 0
300	100	5	85.5	25.4	3.047 0
600	200	5	92.5	31.6	12.39 10
900	300	5	91.2	39.9	27.89 00
1200	400	5	92.5	38.9	74.59 40

Table 1: Effect of scalability on the performance

Here, in Table 1 we can clearly see that as the number of nodes is increased the performance of the algorithm improves by 10% - 30%. Whereas, in COG method the performance improves very less by 5% - 15%. For 20 anchor nodes the performance of success is around 60%, as the no of anchor nodes are increased the success rate rises above 90%.

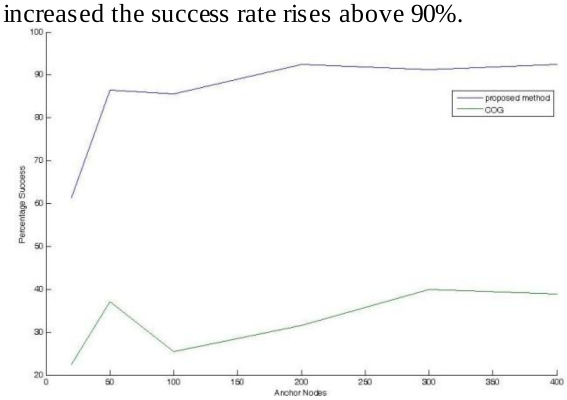

Figure 6: Anchor nodes vs Percentage Beacons

It supports the fact that as the number of beacon nodes in the network increases the calculated location values becomes more close to the original location.

■	Beacon nodes
●	Original node locations
●	Calculated locations using proposed algorithm
●	Calculated locations using COG method

Node specifications in simulated output

Here, fig- 7 shows the sensor network nodes that are used to generate the simulated output.

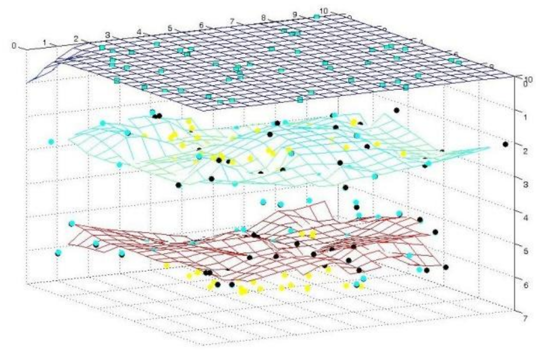

Figure 7: Simulation done by 50 anchor nodes, total number of 150 nodes

The beacon nodes are distributed throughout the first layer. All the other sensor nodes are randomly distributed to respective layers with equal node densities. The uneven horizontal mesh corresponds to the surface beneath.

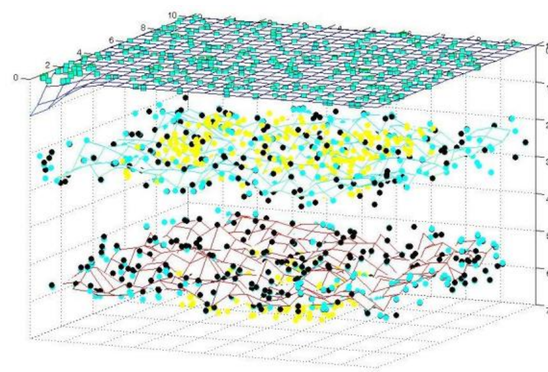

Figure 8: Simulation done by a total of 1200 nodes.

Effect of Radio Range:

No of nodes per layer	**Radio Range(m)**	**% Success in proposed method**	**% Success in COG method**	**Total time(sec)**
100	4	86.9	78.9	3.1720
100	5	85.5	25.4	3.0470
100	6	87.5	46.6	3.3750
100	8	95.6	53.2	4.3440

Table 2: Effect of radio range

As our application is mainly aimed towards the rescue operations so the performance is observed w.r.t. the variations in radio range. Table- 2 gives the simulated results. The above simulation is carried out taking the inter layer separation 3m. As the proposed utilizes both the range-free and range-based strategies there is not much performance change in it. Further, in case of COG method initially when the radio range is very less the performance of COG is quite high, intermediate radio ranges the success rate varies between 25%-50%, as the range of the anchor nodes increases one layer of sensor nodes are affected by multiple layers of beacon nodes above it giving it a increasing success rate.

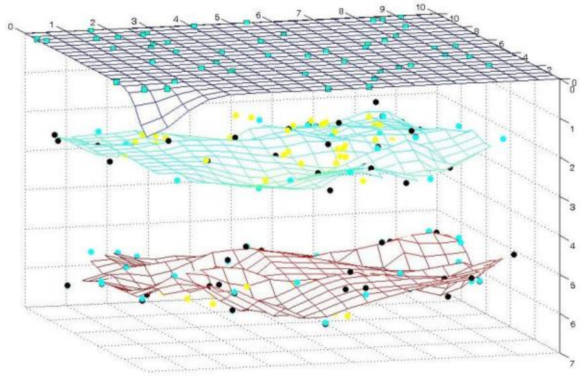

Figure 9: Simulation done taking 150 nodes with radio range 5m

The simulation time taken increases irrespective of the number of sensor nodes as for single layer information of location from multiple layers of beacon nodes are processed.

Effect of Noise:

Radio Range (m)	Noise Factor (SD)	% Success in proposed method	% Success in COG method	Total time(sec)
5	0.005	96	30.8	3.4220
5	0.010	85.5	25.4	3.0470
5	0.015	63.5	30.6	3.3440
5	0.020	65.8	21.5	3.3750
5	0.025	53.8	26.6	3.3750

Table 3- Effect of noise, varying standard deviations.

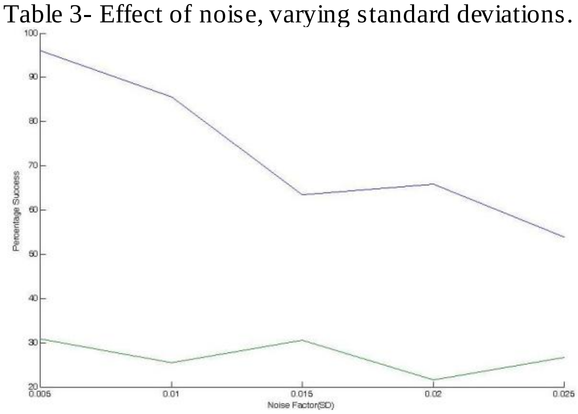

Figure 10-Noise factor vs Percentage success

The noise here is considered to be Gaussian Noise with mean μ =0 and standard deviation σ .Here, we can clearly see that the noise has direct impact on estimation accuracy. As the noise value increases the success rate of the proposed scheme varies between 55% - 95%. Though the success rate drops but still it gives better results than other methods.

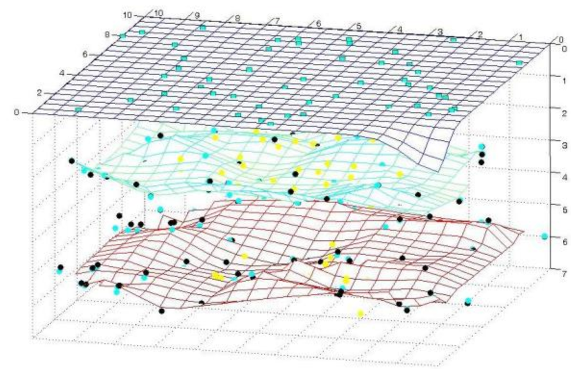

Figure 11: Simulated output taking 150 nodes & standard deviation of 0.005

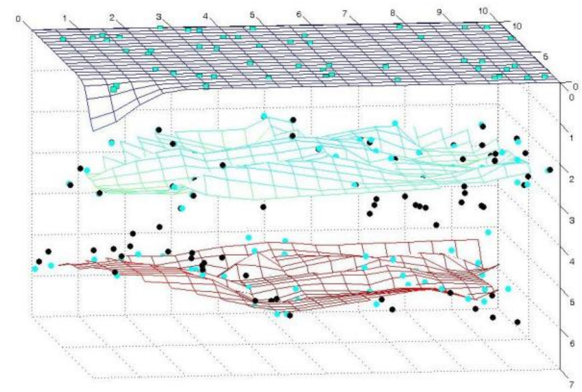

Figure 11: Simulated output taking 150 nodes & standard deviation of 0.025

In COG the noise has very less impact because of the nature of COG estimation of value. As COG method considers the mean of all the locations so a localization error tends to deviate the calculated values very less.

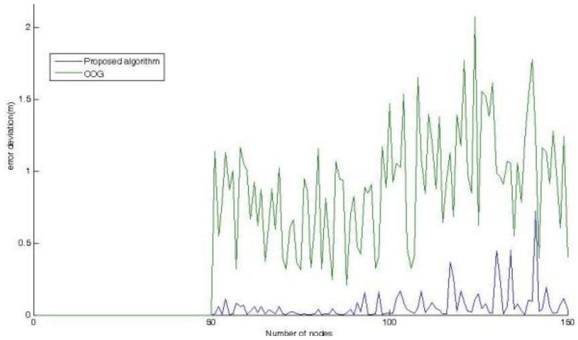

Figure 12: Error deviation vs number of nodes

In the above figure all the beacon nodes are aware of their own location information. So, up to 50 nodes no error in location information. Next layers correspond to 50-100 and 100-150 to layer 2 and layer 3 respectively. We can clearly see that the error is comparatively less in layer 2 than in layer 3. As it's a relative localization scheme the error continues to propagate to lower layers.

Effect of Distance between the layers:

Radio Range (m)	**Distance between Layers**	**Success in proposed method**	**% Success in COG method**	**Total time(sec)**
5	2.0	89.6	62.0	3.4210
5	2.5	86.2	52.3	3.2104
5	3.0	85.5	25.4	3.0470
5	3.5	84.8	34.2	3.4060
5	4	81.3	28.9	3.2190

Table 4: Effect of distance between the layers

Here, the distance between the layers is varied keeping the radio range constant. The effect of interlayer spacing does not affect much of success rate but for the COG method it varies at a considerable mount.

5. Conclusion

The literature survey work has shown that an optimal algorithm has not been defined yet, that employ both the strategies (range-free & range-based) , and thus the development of a new algorithm has to be founded on the specificities of the situations, taking into account the size of the network, as well as the deployment methods and the expected results. Localization algorithms should be designed to achieve low variance as well as low bias as far as possible; at the same time, they need to be scalable to very large network sizes without dramatically increasing energy consumption or computational requirements. We have proposed and demonstrated an algorithm that successfully localizes nodes in a sensor network with noisy distance measurements. The equations for the proposed algorithm were carried out in MATLAB. Simulations showed the relationship between noise and ability of a network to localize itself, at highly noisy environments. The performance stays above 50% i.e. half of the available nodes can be localized with good approximation. We also have depicted the effect of scalability on the performance of the algorithm. Results show that as the scalability of the network increases with the number of beacon nodes; the performance of the algorithm goes high above 90%. The granularity of the areas estimated may be easily adjusted by changing the system parameters which makes the proposed algorithm flexible.Moreover, with one of the ideas proposed, the Bounding cube. This leads to major developments that have been proposed in this thesis which improves significantly to increase the localization accuracy. They do not require much more computational costs and perfectly match the distributed algorithm's requirements. Continuing further, the proposed algorithm operates in a distributed manner by executing the algorithm in different sensor nodes. The propagating trend of the localization procedure provides wave-spreading like characteristic in this algorithm. The proposed algorithm performed very well on the MATLAB simulating environment. We recommend the use of sensor nodes with following characteristics: A dedicated high speed timer is required by RSS ranging. The microcontroller in the sensor nodes is expected to perform additional tasks at moreover; a higher performance processor is highly suggested. These sensor nodes should be capable of performing hybrid localization by introducing the fusion of both range-free ranging and received signal strength RF ranging. Finally, due to the varying scenarios where localization processes come into play, it has been and will continue being an important research field to be explored.

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