

An Area Localization Scheme for Underwater Sensor Networks

Vijay Chandrasekhar and Winston Seah

Networking Department, Institute for Infocomm Research
21 Heng Mui Keng Terrace, Singapore 119613
{vijay,winston}@i2r.a-star.edu.sg

Abstract – For large wireless sensor networks, identifying the exact location of every sensor may not be feasible and the cost may be very high. A coarse estimate of the sensors' locations is usually sufficient for many applications. In this paper, we propose an efficient Area Localization Scheme (ALS) for underwater sensor networks. This scheme tries to estimate the position of every sensor within a certain area rather than its exact location. The granularity of the areas estimated for each node can be easily adjusted by varying system parameters. All the complex calculations are handled by the powerful sinks instead of the sensors. This reduces the energy consumed by the sensors and helps extend the lifetime of the network.

I. INTRODUCTION

Underwater sensor networks (UWSNs) deployed in the oceans will consist of sensors equipped with acoustic modems that enable them to communicate wirelessly with one another. UWSNs can also include unmanned autonomous vehicles working together with the static sensors deployed on the seabed or in midwater, and they would cooperate in the sensing task and send their data to a central sink in a multi-hop manner for real-time processing. The nature of underwater sensor networks is fundamentally different from that of terrestrial sensor networks. Acoustic communications is used instead of RF (Radio Frequency) because RF signals cannot travel far underwater due to severe absorption losses. Underwater acoustic channels are characterized by harsh physical layer environments, where the available bandwidth is severely limited and channels are severely impaired due to multi-path and fading problems. Acoustic signals also travel at five orders of magnitude lower than RF signals, and consequently, the propagation delay is very significant and has a high variance.

Localization is the problem of determining the location of each sensor in a sensor network. In most of the underwater applications mentioned above, it is critical for each node to know its location. The Global Positioning System (GPS) used for locating nodes in terrestrial networks cannot be used in UWSN, as the high frequency radio waves are absorbed by the water and cannot travel far. Several localization schemes have been proposed for terrestrial sensor networks but these localization schemes cannot be directly applied to UWSN due to the distinct nature of the UW channels. Hence, the need to develop new localization schemes that work well in underwater scenarios arises.

II. RELATED WORK

The localization schemes, that have been proposed to date, can be broadly classified into two categories: range-based and range-free. In range-based schemes, the distance or angle measurements from a fixed set of reference points are known. Multilateration techniques are then used to estimate the

location of each sensor node. Range-based schemes use Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) or Received Signal Strength Indicator (RSSI) to estimate their distances to the anchor nodes [1][2].

Range-free localization schemes usually do not make use of any of the techniques mentioned above to estimate exact distances to reference nodes. Some range-free schemes employ multilateration techniques after estimating distances to anchor nodes using hop count information [3]. Other schemes like Approximate Point in Triangle (APIT) [4] and Area Localization Scheme (ALS) [5] use an area based approach for localization in terrestrial sensor networks. Range-free schemes generally offer a less precise estimate of location compared to range-based schemes.

In order to take advantage of the slow propagation speed of sound under water, range-based schemes that use ToA and TDoA are suggested for UWSNs [6][7] and some range-based schemes that use ToA and TDoA have been compared in [8]. However, perfect time synchronization among all the nodes in the system is assumed which greatly simplifies or eliminates one of the two major challenges. Firstly, these schemes are vulnerable to the speed of sound, which is not constant under water. The speed of sound depends on a number of factors like temperature, pressure and salinity. Complicated signal processing techniques would be needed to compensate for this variation. Secondly, time synchronization between nodes is critical for ToA and TDoA approaches. Synchronizing the clocks of nodes is challenging underwater because of the long propagation delays and the harsh physical layer environment in consideration. Time synchronization would also increase the communications overhead and compete for the scarce wireless bandwidth.

III. AREA LOCALIZATION SCHEME

We propose an area-based localization scheme (ALS) for large underwater wireless sensor networks which derives from the terrestrial version [5]. This is a centralized range-free scheme that provides a coarse location estimation of a sensor within a certain area, rather than its exact position. The advantage of this scheme lies in its simplicity, as no TDoA, ToA, RSSI or AoA measurements need to be made by the sensor. More importantly, the clocks of the nodes in the system need not be synchronized, and the scheme is not vulnerable to the varying speed of sound underwater. There are three categories of nodes in ALS, according to their different functions: reference nodes, sensor nodes and sinks.

A. Reference Nodes (Anchor Nodes)

The main responsibility of the reference (or anchor) nodes is to send out beacon signals to help sensor nodes locate

themselves. Reference nodes are assumed to know their locations. In addition, the reference nodes can send out acoustic signals at varying power levels as required. In this paper, we shall use the terms reference node and anchor node interchangeably.

Acoustic signals are susceptible to a wide range of limitations such as attenuation, long propagation delays, multi-path effects, Doppler effects and ambient noise. The spreading loss of acoustic signals under water can be modeled as cylindrical or spherical [9]. The spherical model, which we adopt, has a path loss exponent of 2, and the path loss can be expressed in dB as:

$$TL_{spherical} = 20 \log \left(\frac{R}{R_{1m}} \right) \quad (1)$$

where R = radial distance from the source and R_{1m} = 1 meter is the reference unit distance. In addition, the acoustic waves also undergo attenuation losses which can be modeled by:

$$TL_{att} = \alpha R \quad (2)$$

where α is the attenuation coefficient. For frequencies below 50 kHz, the attenuation coefficient can be approximated by Thorp's equation [10]:

$$\alpha R = 1.0936 \left[\frac{0.1 f^2}{1 + f^2} + \frac{40 f^2}{4100 + f^2} \right] \quad (3)$$

The total propagation path loss is therefore given by:

$$TL_{total} = TL_{spherical} + TL_{att} \quad (4)$$

From the above equations, it can be clearly seen that if the received power is fixed at a certain value, the beacon signal with a higher transmitted power reaches a greater distance. Using the physical layer model described above and the threshold (lowest) power that each sensor can receive, the reference node can calculate the power required to reach different distances. Each reference node then devises a set of increasing power levels such that the highest power level can cover the entire area in consideration. The reference nodes then broadcast several rounds of beacon signals. The beacon packet contains the ID of the reference node and the power level at which the signal is transmitted (which can be simply represented by an integer value, as explained below).

Let the set of increasing power levels of beacon signals sent out by an anchor node be denoted by PS . For now, let us assume that all the anchor nodes in the system send out the same set PS of beacon signals. In the ALS scheme, the sensor node simply listens and records the power levels of beacon signals it receives from each anchor node. In real environments, multi-path and Doppler effects can cause the power levels received by the sensor nodes to vary significantly from the expected power levels calculated by the path loss models in Eqn. (4). Sending out beacon signals in the set PS only once might lead to inaccurate power levels being measured by sensor nodes. As a result, the anchor nodes send out the beacon signals in set PS multiple times. The sensor nodes can then calculate the statistical average (mode or mean) of the received power levels from each anchor node.

Let the number of power levels in set PS be denoted by N_p . Let the N_p power levels in set PS be represented by $P_1, P_2, P_3, \dots, P_{N_p}$. The power levels $P_1, P_2, P_3, \dots, P_{N_p}$ can be represented by simple integers; therefore sensor nodes only need to take note of these integer values that are contained in the beacon packets and the hardware design can be kept simple as there is no need for accurate measurement of the received power level. Let the number of times that the same set of beacon signals PS are sent out be denoted by N_r , also referred to as the number of rounds. The power MP in dB required to cover the entire area is calculated from equation (4). The power LP in dB required to cover a small distance \hat{C} (say 10 m) is also calculated. The values $P_1, P_2, P_3, \dots, P_{N_p}$ are then set to be N_p uniformly distributed values in the range $[LP, MP]$ in the dB scale. The simple procedure followed by the anchor nodes is shown below:

```

1  For i = 1:  $N_r$ 
2      For j=1:  $N_p$ 
3          Send beacon signal at power level  $P_j$ 
4      End
5  End

```

The transmissions by the different anchor nodes do not need to be synchronized. However, they schedule the beacon signal transmissions so as to avoid collisions. The transmitted set of power levels PS need not be the same for all the reference nodes, and can be configured by the user. In addition, the set of power levels PS need not be uniformly distributed too. It is also not necessary for the anchor nodes to know one another's position and levels of transmitted power, but there should be at least one sink or a central agent that stores the location information of all the reference/anchor nodes.

B. Sensor Nodes

A sensor node is a device that monitors the environment. Sensors typically have limited computing capability, storage capacity, communication range and battery power. Due to power constraints, it is not desirable for sensor nodes to make complex calculations and send out information frequently.

B.1 Signal Coordinate Representation:

In the ALS scheme, the sensors save a list of reference nodes and their respective transmitted power levels. The sinks use this information to identify the area in which the sensors reside in. However, if the number of reference nodes is large, the packets containing location information may be long, which might result in more traffic in the network. A naming scheme is hence designed.

The sensor nodes use a signal coordinate representation to indicate their location information to the sinks. Power contour lines can be drawn on a grid based on the set of beacon signal power levels PS transmitted by each anchor node, and their corresponding distances traveled. The power contour lines divide the area in consideration into many sub-regions as shown in Figure 1. Each sub region in the grid can be represented by a unique set of n coordinates, referred to as the signal coordinate from hereon.

Suppose there are n reference nodes, which are referred to as R_1, R_2, \dots, R_n . For a sensor in the grid, let the lowest transmitted power levels it receives from the n reference nodes be S_1, S_2, \dots, S_n respectively. S_1, S_2, \dots, S_n are simple integer numbers indicating the different power levels rather than the actual signal strengths. The mappings between the integer levels and actual power values are known only by the reference nodes and sinks. A signal coordinate is defined as the representation $\langle S_1, S_2, \dots, S_n \rangle$ such that each S_i , the i^{th} coordinate, is the lowest power level received from anchor node i .

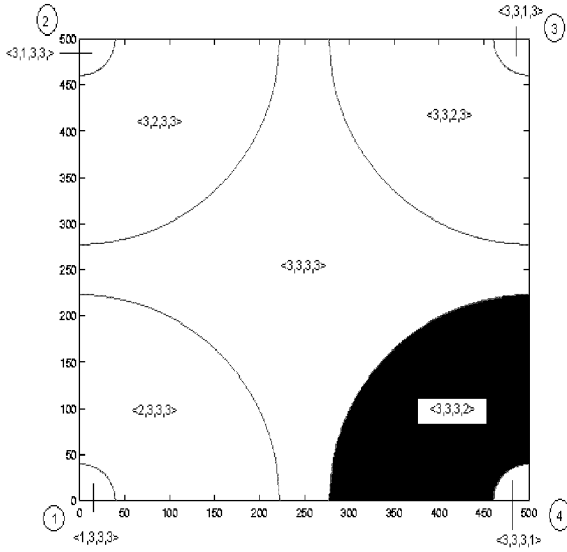


Figure 1. An example of the ALS under ideal isotropic conditions. Shaded region is $\langle 3, 3, 3, 2 \rangle$

For example, consider a square area with anchor nodes at the four corners as shown in Figure 1. In this case, the set of power levels PS that form the grid is the same for all the four anchor nodes and there are three power levels in the set PS . The smallest power level in the power set PS is represented by the integer 1 while the highest power level is represented by the integer 3. For each node, the contour lines represent the farthest distances that the beacon signals at each power level can travel. Contour lines for beacon power levels 1 and 2 are drawn. The power level 3 for each corner anchor node extends beyond the corner that is diagonally opposite to it and so, its corresponding contour line is not seen on the area. Thus, for each anchor node, the two contour lines corresponding to power levels 1 and 2 divide the area into three regions.

For a sensor node in the shaded region, the lowest power level received from anchor nodes 1, 2 and 3 is 3. The sensor node also receives beacon signals at power levels 2 and 3 from anchor node 4. So, the lowest power level received by the sensor from anchor node 4 is 2. As a result, the shaded region in the figure can be represented by the unique signal coordinate $\langle 3, 3, 3, 2 \rangle$. Similarly, every other region in the square area can be represented by a unique signal coordinate, as shown in the figure. As stated in the signal coordinate definition, the lowest power level received from anchor node i forms the i^{th}

coordinate of the signal coordinate. Sensors use this unique signal coordinate to identify the area in which they are located.

B.2 Algorithm

In the ALS scheme, a sensor node simply listens to signals from all reference nodes and records the information that it receives from them. A sensor node at a particular location may receive localization signals at different power levels from the same reference node, as illustrated in the example above. The sensor measures its signal coordinate and stores this information to be forwarded to the sinks when required.

Let the signal coordinate of a node be denoted as $\langle S_1, S_2, S_3, \dots, S_n \rangle$ where n is the number of anchor nodes. A sensor node uses variables $L_{11}, L_{12}, L_{13}, \dots, L_{1Nr}$ to represent the lowest power levels received by the sensor from anchor node i during rounds 1 to Nr . Let the number of anchor nodes be n . Initially, all the values $L_{11}, L_{12}, L_{13}, \dots, L_{1Nr}, L_{21}, L_{22}, L_{23}, \dots, L_{2Nr}, \dots, L_{n1}, L_{n2}, L_{n3}, \dots, L_{nNr}$ are set to zero which imply that the sensor nodes have not received any signals from the reference nodes.

After initialization, the sensor nodes start an infinite loop to receive beacon messages from anchor nodes and follow the algorithm shown below. Since a reference node sends out several rounds of signals, the sensor node may hear multiple rounds of beacon signals from the same reference node. If the sensor receives a signal from reference node i for the first time during round j , it sets L_{ij} to be the lowest received power level for that round; otherwise, if the received power level from anchor node i in round j is lower than the value stored in L_{ij} , then L_{ij} is set to the new lowest received power level. After all the anchor nodes have sent all beacon messages, the power levels L_{i1} to L_{iNr} on each sensor represent the lowest power levels received from anchor node i during rounds 1 to Nr respectively.

Initialization:

```

1 for i=1 to n
2   for j = 1 to Nr
3      $L_{ij} = 0$ 
4   end
5 end

```

Loop:

```

1 receive a message
2 if (the message is from reference node  $i$  during round  $j$ )
3   if ( $L_{ij} = 0$  || received power level  $< L_{ij}$ )
4      $L_{ij} =$  received power level
5   end if
6 end if

```

Each reference node sends out beacon signals at all the power levels in the set PS Nr times (Nr rounds). Hence, the lowest signal power level received by a sensor from an anchor node need not be the same for all the rounds 1 to Nr , i.e. all the values L_{i1} to L_{iNr} need not be the same. One is then faced with the problem of deciding which value L_{ix} to pick as S_i , the i^{th} element of the signal coordinate. Hence, a threshold value $CONFIDENCE_LEVEL$ is defined. This parameter represents the confidence level with which the values S_1, S_2, \dots, S_n can be estimated. For example, by setting this value to 80% of Nr in our simulations, if there is a power level L_{ix} that occurs with

frequency greater than $CONFIDENCE_LEVEL$ in the set $\{L_{i1}, \dots, L_{iNr}\}$, then L_{ix} is selected as the i^{th} element in the node's signal coordinate, i.e. $S_i = L_{ix}$. If there is no power level with frequency greater than $CONFIDENCE_LEVEL$, then all the distinct power levels in the set $\{L_{i1}, \dots, L_{iNr}\}$ are considered possible candidates of the i^{th} element in the signal coordinate.

The above concept is illustrated by a few examples here. The shaded area in Figure 1 represents the case of the signal coordinate $\langle 3, 3, 3, 2 \rangle$. In this case, there exists power levels which occur with frequency greater than $CONFIDENCE_LEVEL$ in the set $\{L_{i1}, \dots, L_{iNr}\}$, for each signal co-ordinate S_i .

Now, consider the other scenario where the lowest power level received from anchor 1 during the Nr rounds of beacon messages oscillates between 2 and 3. If the power levels 2 or 3 do not occur with frequency greater than $CONFIDENCE_LEVEL$ in the set $\{L_{i1}, \dots, L_{iNr}\}$, both 2 and 3 can then be considered possible candidates for S_i . The shaded region in black in Figure 2 represents this case: $\langle \{2, 3\}, 3, 3, 3 \rangle$. There also could be scenarios where no beacon packets are received from an anchor node. For example, if no information is available on the first coordinate, the signal coordinate region $\langle \{1, 2, 3\}, 3, 3, 3 \rangle$ is considered as the area estimate. The region $\langle \{1, 2, 3\}, 3, 3, 3 \rangle$ is represented by the union of the red and black regions in Figure 2.

Thus, each coordinate S_i in the signal coordinate $\langle S_1, S_2, S_3, \dots, S_n \rangle$ need not be a unique value, but could be represented by a set of values as shown in the examples here.

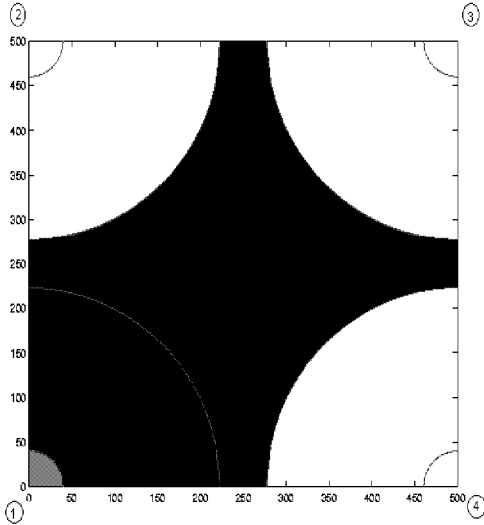


Figure 2. $\langle \{2, 3\}, 3, 3, 3 \rangle$ and $\langle \{1, 2, 3\}, 3, 3, 3 \rangle$

C. Sink

A sink collects information from sensor nodes and then processes the information to estimate the area in which the sensor is located. A sink usually has much higher capabilities in computing and processing than a sensor node, and it determines where the sensor is based on the signal coordinate information obtained from the sensor. One assumption of the ALS scheme is that the sink knows the positions of all the

reference nodes and their respective transmitted power levels, through direct communications with the reference nodes, or other means. Together with the physical layer model and signal propagation algorithms, the sink is able to derive the map of areas divided by all the transmitted signals from the reference nodes. With the map and the signal coordinate information, the sink can find out which area a sensor is in when receiving data and location information (signal coordinate) from it. In the ALS scheme, the signal propagation model chosen plays an important part in the estimation accuracy. For different networks, different signal propagation models can be used to derive the signal map according to the physical layer conditions. Using the same network topology shown in Figure 1, an irregular signal model could divide the whole area into many different shapes, as shown in Figure 3.

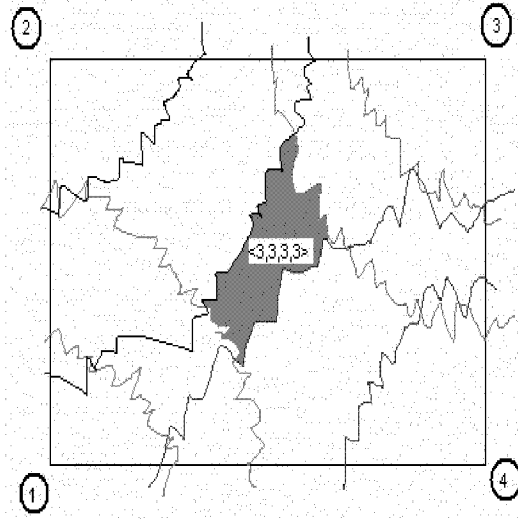


Figure 3. ALS example using an irregular signal model

IV. GRANULARITY

The size of the region in which a sensor is estimated to be in is based on its position and the signal coordinate that it measures. *Granularity* is defined as the average of the area estimates of all the sensors in the network. As it is unlikely that all nodes will lie in their estimated areas, another metric *average accuracy* is defined to measure the percentage of nodes in the network that lie in their estimated areas.

Both granularity and average accuracy are affected by the following four parameters:

- Number of reference nodes n
- Positions of the reference nodes
- Number of transmitted power levels N_p in the set PS
- Transmitted power levels $P_1, P_2, P_3, \dots, P_{N_p}$

To achieve a desired granularity, the user may choose to change one or more of the four parameters. The number and positions of reference nodes are usually determined at the time of deployment of the sensor network. So, these two parameters should be carefully designed by the network administrator before the deployment of the network. The granularity can be

changed after the deployment of the network by adjusting the number of transmitted power levels and the transmitted power at each level for the reference nodes.

Different strategies are employed to increase granularity in ideal and non-ideal environments. An ideal environment is defined as one where the attenuation of acoustic signals follows the predicted path loss model (spherical in our case) very closely and the fading and shadowing effects are insignificant. On the other hand, a non-ideal environment is one where fading and shadowing effects are significant.

Let us assume that the N_p power levels transmitted by each anchor node are uniformly distributed in the range $[LP, MP]$ as described in section III.A. Increasing the number of power levels N_p would then imply reducing the power difference between adjacent power levels.

Under ideal or close to ideal conditions, most nodes measure their signal coordinates correctly because of the very low variance in power levels of the beacon packets received. For such conditions, granularity can be increased by just increasing the number of power levels, resulting in smaller regions being created in the grid, thus increasing granularity.

Under non-ideal conditions, increasing the number of power levels would not increase granularity as in the ideal case. As the power difference between adjacent levels decreases, fading and shadowing effects cause the received signal strength to vary by more than the difference in adjacent power levels. As a result, fewer nodes will measure their signal coordinates correctly. Consequently, wrong measurement of signal coordinates will lead to wrong area estimates.

The number of sensor nodes measuring their signal coordinates incorrectly can be reduced by having a small number of power levels, and concurrently maintaining a significant power difference between adjacent power levels. However, fewer power levels result in larger regions being created in the grid, thus leading to reduced granularity. To increase granularity, we propose performing ALS multiple times, but with a small distinct set of power levels PS for each run and a significant power difference between adjacent power levels. Each round of ALS gives an area estimate for the sensor node based on its signal coordinate. The intersection of the areas obtained from the different rounds of ALS can be used to estimate the final area in which the sensor is located.

Figure 4 shows an example of ALS done with six rounds i.e. six distinct PS sets, where each set contains three distinct power levels with significant difference between adjacent power levels. For the first three rounds, the anchor nodes at the four corners send out beacon signals, and for the next three, the anchor nodes at the mid-points of the four sides send out beacon signals. Each color represents a set of power contour lines. Figure 4 represents the final grid obtained by overlapping the contour lines from all the six rounds. The final area estimate of a sensor is the intersection of the areas obtained from all the rounds that have been carried out. If the areas obtained from all the rounds completed do not intersect, the largest intersecting area obtained is considered as the area estimate. Therefore, the final area estimate of each sensor node is one small region or a combination of many small regions in

the final grid shown here. The sensor nodes simply measure their signal coordinates for each round of ALS, and forward it to the sink which does all the complex computations.

V. RESULTS AND OBSERVATIONS

A. Performance metric for ALS

The metrics, *average accuracy* and *granularity*, are defined in Section IV. High levels of both accuracy and granularity are desired. However, average accuracy begins to degrade as granularity increases, as the probability of estimating the location of a node correctly in a smaller region decreases. Hence, the performance metric used to evaluate the ALS is the average accuracy normalized with respect to the average area estimate (granularity) i.e. Average Accuracy / Average Area Estimate.

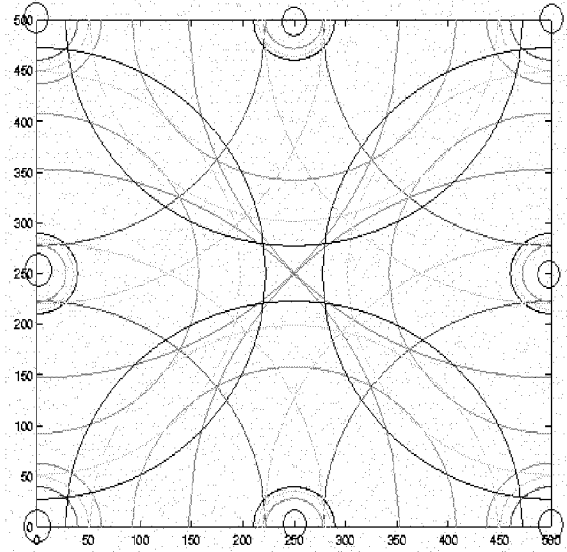


Figure 4. Sample grid with 6 rounds of ALS

B. Simulation scenario

The QUALNET 3.8 simulation environment is used to evaluate the performance of ALS. The system parameters used in our simulation scenario are described below.

- ◆ Area: Square area of size 500m×500m is considered.
- ◆ Physical layer: Spherical spreading model with attenuation losses is considered. In the non-ideal case, Rayleigh fading and shadowing losses are also considered.
- ◆ Transmission Frequency: Acoustic transmission frequency is set to 15 kHz.
- ◆ Node placement: A wireless sensor network with 500 nodes (eight of which are anchor nodes) is considered. The sensors are placed randomly throughout the area, and the eight anchor (reference) nodes are positioned at the four corners and at mid-points of the four sides of the square area. While there are eight anchor nodes in the network, only four send out beacon signals during each ALS round.
- ◆ Anchor to Node Range Ratio (ANR): This parameter refers to the average distance an anchor beacon signal travels divided by the average distance a regular node

signal travels. The range of sensors is set to 50m, while the transmission range of anchors is set to 1000m i.e. ANR is set to 20. The transmission range of the anchor nodes is enough for the beacon signals to cover the whole area.

- ◆ **Node Density (ND):** The node density refers to the average number of nodes per node range area. This value is close to 13 for our system.
- ◆ **Anchor Percentage (AP):** The anchor percentage refers to the number of anchors divided by the total number of nodes. We consider systems with low AP: 1.6% (8/500).
- ◆ **Receiver Threshold Power:** The receiver threshold power refers to the lowest signal strength of a packet that a node can receive. The value is set to -50 dBm.
- ◆ N_r refers to the number of times each beacon signal is sent out by a reference node. This parameter is set to 20.
- ◆ **Mobility:** None. All the nodes are assumed to be static.
- ◆ **CONFIDENCE_LEVEL:** 80%.

C. ALS under non-ideal conditions

The ALS is evaluated under both ideal and non-ideal conditions for 10 rounds. The results on Average Accuracy/Average Area Estimate is then plotted against the number of rounds of ALS, as shown Figure 5 and summarized in TABLE 1.

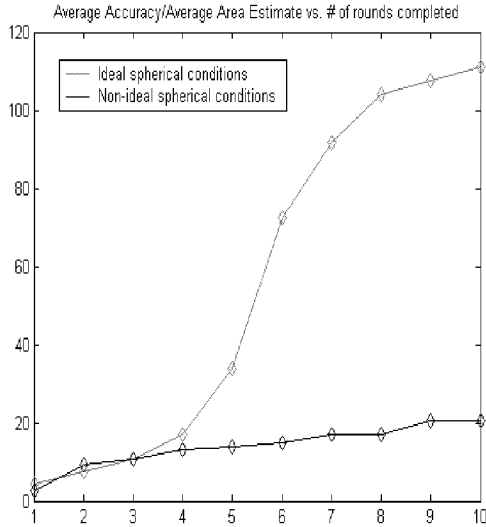


Figure 5. Average Accuracy/Average Area Estimate

# of rounds finished			Ideal spherical conditions		Non ideal spherical conditions	
	LP	MP	Avg. Area Est. as % of grid size	% of nodes that lie in their area estimate: Accuracy	Avg. Area Est. as % of grid size	% of nodes that lie in their area estimate: Accuracy
1	-15	15	23.7	100	36.5	96.9
2	-14	16	13.3	100	10.3	94.3
3	-13	17	9.4	100	8.6	90.3
4	-12	18	5.9	100	6.6	85.7
5	-11	19	2.9	100	5.8	80.1
6	-15	15	1.4	100	4.9	73.4
7	-14	16	1.0	100	4.1	69.3
8	-13	17	0.96	100	3.8	65.3
9	-12	18	0.93	100	3.1	63.2
10	-11	19	0.82	100	3.0	61.2

TABLE 1: DATA FOR THE NON-IDEAL CASE

Under ideal cases, the average accuracy is always 100%, as all nodes detect their signal coordinate correctly. For the non-ideal case, as the number of rounds increases from 1 to 10, average accuracy decreases from 96.9% to 61.2% (TABLE 1). This is because a wrong signal coordinate measured in any one of the rounds would result in the final area being estimated incorrectly, as the intersection of areas from all rounds is considered in the final area estimate. On the other hand, granularity increases i.e. the average area estimate decreases from 36.5% of the grid size to 3.0% of the grid size (TABLE 1). The granularity increases as the final intersection regions for all sensors get smaller and smaller as the number of rounds increases.

The performance metric (Average Accuracy/Average Area Estimate) shown in Figure 5 increases, and starts to flatten out as the number of rounds increases. The performance metric increases as the decrease in average area estimate is greater than the decrease in average accuracy after each additional round of ALS. The performance flattens out because of the quantization of power levels, and the constraint of maintaining a significant difference between adjacent power levels (15 dB in this case). The ALS can be stopped once desirable accuracy levels and granularity are obtained.

Nodes that are closer to boundaries are more prone to measuring the wrong signal coordinate. An analysis was carried out to investigate the error patterns of nodes that did not lie in their estimated areas. It was observed that nodes, whose locations were estimated incorrectly, were very likely to be in an adjacent region of comparable area size in the final grid. It was observed that close to 96% of nodes lay in the estimated region, or in an adjacent region of comparable size.

The centroid of each sensor's areas estimate can be considered its location. Assuming the centroids as the location estimates, it was observed that the average error was close to $0.75 \cdot R$ (transmission range) for the scenario in consideration.

D. Comparison with other area localization schemes

The performance of ALS after 10 rounds is compared to two other range-free area localization schemes, namely, PIT (Point in Triangle) and APIT (Approximate Point in Triangle).

In the PIT and APIT schemes, a node chooses a set of three audible anchors and tests whether it is inside the triangle formed by connecting them. The theoretical method used to determine whether a point is inside a triangle or not is called the Point-In-Triangle (PIT) test [4]. The PIT test can be carried out only under ideal physical layer conditions, when every node in the network is mobile and can move around its own position. Due to the infeasibility of conducting such a test, an APIT (Approximate Point in Triangle) test is proposed [4]. The PIT or APIT tests are carried out for different triangular anchor combinations until all combinations are exhausted. The information is then processed by a central server to narrow down the possible area in which a target node resides.

Figure 6 shows all the possible triangles for the given configuration of the eight anchor nodes. There are 52 triangles in total ($\binom{8}{3} - 4$). The sensor nodes determine whether they are inside or outside of each of the 52 triangles, and the final area estimate computed is a small region or combination of regions on the grid. Since PIT and APIT are both area localization schemes, their performance are compared with ALS using the (Average Accuracy/Average Area Estimate) metric. The following five cases are compared and the results presented in Figure 7.

- i. ALS under ideal physical layer conditions after ten rounds
- ii. PIT under ideal physical layer conditions
- iii. APIT under ideal physical layer conditions
- iv. ALS under non ideal physical layer conditions after ten rounds
- v. APIT under non ideal physical layer conditions

The PIT and APIT schemes are carried out under ideal conditions to establish the performance limits that can be achieved with the APIT algorithm under non ideal conditions. For the given simulation scenario, it is observed that the ALS under ideal conditions after 10 rounds outperforms PIT after ten rounds. Under non-ideal conditions, it is observed that ALS performs much better than APIT. This is primarily because fluctuating RSSI values causes a number of APIT tests to be incorrect. It is observed that only around 60% of the 52 APIT tests are correct for each sensor. This results in large area estimates on the grid. Thus, lower accuracy levels and larger area estimates cause the performance of the APIT algorithm to suffer. The ALS, on the other hand, is more resilient to fading and shadowing due to the significant difference between adjacent beacon power levels in each round.

For the scenario in consideration, the area estimate obtained from the intersection of just 10 regions for ALS, one from each round, results in a better performance than APIT, which considers the intersection of 52 regions. Thus, ALS achieves the desired performance level as APIT at a much lower computational cost. The computational complexity in number of areas is given by $O(Nr)$ for ALS and $O(NC3)$ for APIT.

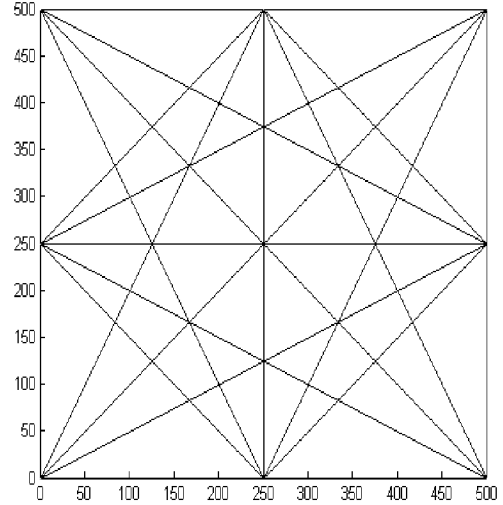


Figure 6. Grid for PIT and APIT schemes with 8 anchor nodes: 4 at corners and 4 at mid-points of sides

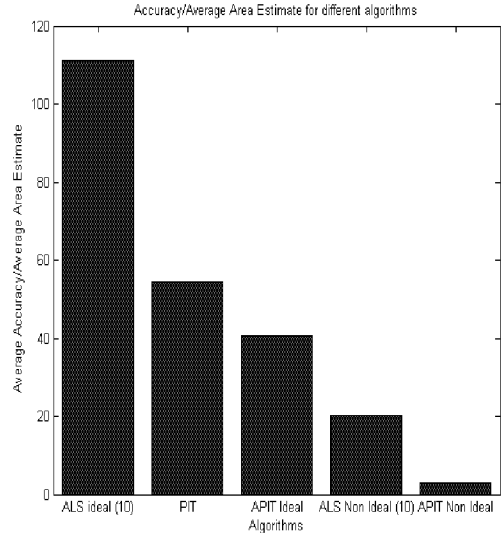


Figure 7. Average Accuracy/Average Area Estimate for different algorithms

VI. CONCLUSION

In summary, the ALS provides a coarse estimation of the location of a sensor within a certain area rather than the exact position. The sensors simply record the signal levels received from reference nodes, while the sinks carry out most of the complex computations. The granularity of the area estimates can be increased easily by modifying system parameters. The simulations results show that ALS is a very promising scheme as more than 96% of nodes are located in their estimated areas or in an adjacent region.

REFERENCES

- [1] P. Bahl and V. Padmanabhan, RADAR: An In-Building RF-based User Location and Tracking System, Proceedings of IEEE INFOCOM, Mar 26-30 2000, Tel Aviv, Israel.
- [2] D. Niculescu and B. Nath, Ad Hoc Positioning System (APS) Using AOA, Proceedings of IEEE INFOCOM, Apr 1-3 2003, San Francisco, CA, USA.
- [3] D. Niculescu, et al, DV based positioning in ad hoc networks. In Journal of Telecommunication Systems, Kluwer, 22(1-4), pp. 267-280, Jan 2003
- [4] T. He, et al, Range-Free Localization Schemes for Large Scale Sensor Networks, Proceedings of MobiCom 2003, Sep 14-19 2003, San Diego, CA, USA.
- [5] Q. Yao, et al., An Area Localization Scheme for Large Wireless Sensor Networks, Proceedings of the IEEE 61st Semiannual Vehicular Technology Conference (VTC2005-Spring), May 30 – Jun 1, 2005. Stockholm, Sweden.
- [6] J. Heidemann, Y. Li and A. Syed, Underwater Sensor Networking: Research Challenges and Potential Applications, Technical Report ISI-TR-2005-603, USC/Information Sciences Institute, Jul 2005.
- [7] J. Kong, et al, Building Underwater Ad-hoc Networks and Sensor Networks for Large Scale Real-time Aquatic Applications, Proceedings of IEEE Military Communications Conference (MILCOM '05), Oct 17-20 2005, Atlantic City, GA, USA
- [8] Jose Garcia, Positioning of sensors in Underwater Acoustic Networks, Proceedings of the MTS/IEEE OCEANS Conference, Sep 19-23, Washington DC, USA.
- [9] X. Lurton, An Introduction to Underwater Acoustics – Principles and Applications, Springer, Praxis Publishing, 2002
- [10] W. H. Thorp, Analytic Description of the Low-Frequency Attenuation Coefficient, Journal of the Acoustical Society of America, Vol. 42, No. 1, 1967.