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Edge-based Cooperative Localization in Wireless Sensor Networks

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Abstract: Localization is important in Wireless Sensor Networks (WSN) applications. When a sensor is deployed, its sensor data is often of limited use unless the position of the sensor is known when the measurement was taken. This research is conducted to solve the grid spacing of more than 30 meters because this grid spacing setup would lead to some nodes having insufficient beacon messages (i.e. 4 or more) to localize their positions. If only a portion of nodes is localized, then a so-called cooperative localization can be used. These experiments use a probabilistic simulation environment which allows large numbers of experiments to be run to reduce the random effects from the imprecise nature of Received Signal Strength Indicator (RSSI) ranging. These experiments are undertaken where a flight path attempts to localize blind nodes just around the edges of the sensing areas by using a mobile anchor, and then to use cooperative localization to progressively localize all the other nodes. The parameters used are number of reference node, their uncertainty for virtual anchors, quality of range estimates and 3D - geometry. The flight path consists of three loops at alternate 10m, 13m, and 10m heights, with these loops spaced 50 m apart, and the total length is 4.8 km Edge-based path planning can use localize a ring around the edge of the sensing area, but in order for this localization to propagate into a central area with no mobile beacon messages, an impractically high node density is required.

Keywords: wireless sensor network; localization; probabilistic multilateration; 3-D geometry; beacon arrangement; angle; height

1.0 INTRODUCTION

Localization is important for many Wireless Sensor Networks (WSN) applications. When a sensor is deployed, its sensor data is often of limited use unless the position of the known when the measurement was taken. While technologies like Global Positioning System (GPS) are now relatively cheap, the additional circuitry, antennas, energy use and computational resources are not always suitable for low cost, low-energy sensors, especially where the sensor is static and only needs to be localised once. Additionally, GPS is not always available due to buildings, trees or other obstructions. For this reason, there is keen interest in other methods for localizing sensors.

This paper considers a motivating scenario where the sensor nodes are carried by an aircraft and are then dropped and randomly scattered within the sensing region such as in the application of bushfire monitoring [1]. In this scenario, these nodes are not guaranteed to land at particular locations or in particular orientations. They might be on the ground or at some non-zero elevation, e.g. in a tree. The nodes should be lightweight and rugged enough to minimize the possibility of being damaged during their deployment [2].

When a sensor is deployed in the sensing region, its sensor data is often of limited use unless the position of the sensor is known when the measurement was taken. While localization technologies like GPS are now relatively cheap, the additional circuitry, antennas, energy use and computational resources are not always suitable for low cost, low-energy sensors, especially where the sensor is static and only needs to be localized once. Additionally, GPS is not always available due to occlusion by buildings, trees or other obstructions. While it would be technically possible to add GPS on each node for accurate localization, it is not cost effective for very low-cost nodes.

Instead, localization can be achieved by using the same aircraft to act as a mobile anchor. The aircraft can be equipped with GPS and can broadcast its position at regular intervals along a specific trajectory. The deployed sensor nodes are blind nodes [3].

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The phase of this research is to solve the grid spacing of more than 30 meters would lead to some nodes having insufficient beacon messages (4 or more) to localize their position. If only a portion of nodes are localized, then so-called cooperative localization can be used. This is where the newly localized sensor nodes (called local anchors) broadcast their own beacons with their estimated position, and these are used, along with the earlier mobile anchor beacons, to estimate positions by the remaining blind nodes. This process may iterate for several generations until all nodes are localized.

2.0 RELATED WORK

Cooperative localization is a popular approach for solving node localization in large WSN deployments. It can significantly outperform anchor-only conventional localization techniques which require sufficient anchors for each individual node.

In [4], a distributed approach with iterative multilateration has been proposed for cooperative localization. Once the blind nodes establish their estimated position, they become anchors. A new anchor will broadcast its estimated position to other neighboring nodes. This is an iterative process until all blind nodes can be localized using at least three reference nodes. The advantage of this implementation is to reduce the communication cost since this repeating process only involves the local neighborhood. Unfortunately, one drawback is it suffers from the error propagation. These new anchors inherit the estimation error produced from the first round of the localization process. Thus, these errors are propagated to other nodes and errors get amplified. Accumulating errors may render results useless if there are excessive iterations in the algorithm.

The author in [5] proposed a mechanism for choosing the reference nodes carefully by considering the topology so that the accumulated error could be reduced. Due to the error propagation problem from the erroneous estimates of the new anchors or virtual anchors that receives information from multiple beacons, it contains of a degree of uncertainty in their estimation. Thus, the research in [5] is focused on determining which combination of the references could produce the best performance. The algorithm started with choosing an appropriate utility function to determine how useful a node is for cooperative localization. The best nodes maximize the accuracy subject to constraints given by the node's limited processing capacity. The parameters used are number of reference node, their uncertainty for virtual anchors, quality of range estimates and geometry. The selection procedure starts by performing an exhaustive search. It will evaluates the combination (coalition value) for sets of anchors, and then the set with the largest coalition value will be chosen. However, this process leads to the exponential search time since the number of combinations is very large. They considered a low density scenario with a small number of candidate nodes and so can use an exhaustive search. The paper concluded that higher coalition values lead to more accurate position estimates with improvement between 39% to 51% with respect to closest distance and random choices for anchors.

Inter-node range-based measurement for the location estimation is used in [6]. The optimization problem of determining the blind node's position is formulated such that it will be consistent with the inter node range measurement and the anchor node's position. Localization using cooperative localization also has been discussed in [5]. The author proposed a probabilistic, constraint-based approach robust to range measurement inaccuracies. The estimated position of the nodes is updated by intersecting the Probability Distribution Function (PDF) constraints with its old PDF estimation.

For the iterative inter-blind-node cooperative localization in our research, the experiment will be conducted by simulating several generations of blind nodes that need to be localized, starting from a small set of anchors, e.g. from a short path length airborne mobile anchor. This will investigate whether cooperative localization can complete localization over a sensing area when not all nodes are localized by mobile beacons. The use of cooperative localization with mobile anchors has not been previously reported.

Motivated by this factor, we will investigate the relative localization performance of adding inter-blind node range estimates to anchor range estimates. Inter-blind node localization is implemented to localize blind nodes with insufficient beacon packets to localize. The other benefit of cooperative localization is to reduce the travel distance of the mobile anchor as a trade-off between the energy expended and localization accuracy. The major issue is understanding the relative localization performance of adding inter-blind node range estimates to anchor range estimates. For example, how does error grow with each generation of cooperatively localized nodes.

3.0 METHODOLOGY

This paper investigates two different scenarios for using cooperative localization. In the first scenario, a square grid with a spacing of 50 m is used with different densities of blind nodes. The usefulness of cooperative localization for "filling in the gaps" in the square grid is examined. In the second scenario, a flight path only around the outside edge of the sensing area is examined, to see if cooperative localization can be used to work from the outside of the area to the center, localizing nodes, generation by generation.

The experiments here use a number of blind nodes spread through the sensing region, including some in unfavorable positions near the region edge. The experiments will investigate not just the average accuracy, but also how accuracy varies across the sensing region. These experiments use a probabilistic simulation environment (Volume Probabilistics Multilateration-VPML) [3] which allows large numbers of experiments to be run to reduce the random effects from the imprecise nature of RSSI ranging.

A. Volume based Probabilistic Multilateration Localization (VPML).

Given a path loss $\hat{P}i$, a PDF of possible distances from beacon *i* can be calculated;

$$\hat{P}i = Po + 10n\,[\log \hat{d}i - logdo] + \hat{r}\sigma p \quad (1)$$

Assuming the reference distance used for the experimental measurement, do is 1 metre, then $logdo = 0$

$$\log \hat{d}i = \frac{\hat{P}i - Po}{10n} - \frac{\hat{r}\sigma p}{10n} \quad (2)$$

Thus $\log \hat{d}i$ can be represented as a PDF of RSSI:

$$\log \hat{d}i = \frac{Pi - Po}{10n} - \hat{r}\sigma d \quad (3)$$

where, $$\sigma d = \frac{\sigma p}{10n} \quad (4)$$

Equation 3 gives a PDF of the likelihood of a particular log-distance for the range, given a path loss value. To be useful, we need to convert to a PDF of distance, not log distance. To convert to a PDF of $\hat{d}i$, we add a correction factor. It must be true that the probability of the real range being between di and di+Δ must be the same in both cases.

$$PDF\ (\log di)\ x\ [\log(\hat{d}i + \Delta) - \log(\hat{d}i)] = PDF\ (di)\ x\ (\hat{d}i + \Delta - di) \quad (5)$$

so

$$\begin{aligned} PDF\ (di) &= \frac{\log(\hat{d}i+\Delta) - \log(\hat{d}i)]}{\Delta}\ PDF \log di \\ &= \frac{d}{\hat{d}i}\left(log\hat{d}i\right) PDF \log di \\ &= \frac{1}{\hat{d}i} PDF \log di \end{aligned} \quad (6)$$

PDF of $\log di$ is a Gaussian with mean $(\mu) = \frac{Pi-Po}{10n}$ and standard deviation (σ) of σd. Using equation 6, we can define;

$$PDF(\log di) = \frac{1}{\sigma\sqrt{2\pi}}\ e^{-\frac{(\log \hat{d}i - \mu)^2}{2\sigma^2}}$$

Thus,

$$PDF\ (di) = \frac{1}{\hat{d}i\ \sigma\sqrt{2\pi}}\ e^{-\frac{(\log \hat{d}i - \mu)^2}{2\sigma^2}} \quad (7)$$

For the multiple beacons, the probability that the blind node is $\hat{d}i$ away from beacon i for all i, is conventionally calculated using the product of the PDFs. Here, we calculate the joint PDF based on the product of individual PDFs as in equation (7). The probability of being at a certain position is the probability of being a certain range from beacon 1 and being a certain range from beacon 2, etc.

Thus;

$$PD(x,y,z) = \prod_i PDFi\ (x,y,z) \quad (8)$$

where $PDFi$ is the PDF of being distance *d* from beacon *i* while PD is the un-normalized joint PDF that the blind node is a certain distance from beacon 1 and a certain distance from beacon 2, until all distances from each beacon *i* are estimated. The actual PDF would require the PDF to be divided by the volume integral of the function above to normalize the total likelihood of being anywhere in the volume to 1. However, we are only looking for the maximum value of the joint PDF.

The maximum of the un-normalized joint PDF will be at the same location as a PDF normalized over the whole volume. An optimization approach can then be used to find the point where PD(*x,y,z*) is a maximum, and this is the estimated position. This is the conventional approach to probabilistic localization, as described in [12]. This conventional approach, however, can be improved by closer examination of the geometry.

In the above formulation, each PDF is a function of a single variable, distance. Given that we are searching for the best point in a 3-D space, it could also be argued that we should use a PDF based on volume, not distance. Given a PDF(d) based on distance from a beacon, the PDF(x,y,z) that the blind node at a particular point at that range can be calculated.

A point at a range of d in the one-dimensional PDF corresponds to the surface of a sphere, radius d, centred at the beacon. The probability that the blind node is in an infinitesimal interval d+Δd in the 1-D PDF corresponds to the probability that the blind node is in a spherical shell, inner radius d, outer radius d+Δd. The volume of the shell is surface area times thickness, $4\pi d^2 \Delta d$. Since this shell volume increases with d^2, the volumetric PDF in 3-D will also scale with d^2 compared to the linear PDF. In particular, the volumetric PDF at a particular point on that sphere is $\frac{PDFi\ (d)}{4\pi d^2 \Delta d}$

Again, ignoring constants (4π) and Δd, this gives a relative volumetric PDF for one beacon range of:

$$PDFVi = \frac{PDFi}{di^2} \quad (9)$$

Then a new joint PDF for being at a certain point based on all the range estimates is:

$$PV(x,y,z) = \prod_i \frac{PDFi\ (x,y,z)}{di^2} \quad (10)$$

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In other words, we further scale each PDF by a factor of di^2 before multiplying them together. Here, we investigated which of $PD(x, y, z)$ and $PV(x, y, z)$ works best. In both cases, we used simple gradient descent convex function optimization to find the maximum value of the joint PDF, starting from the DML estimated position. This gives the (x, y, z) which maximizes PD or PV. This paper explores the geometrical sensitivity and the airborne trajectory using the examination of VPML.

3.1 Edge-Based Cooperative Localization (Experimental Setup)

In this section, experiments are undertaken where a flight path attempts to localize blind nodes just around the edges of the sensing area using a mobile anchor, and then to use cooperative localization to progressively localize all the other nodes. The flight path consists of three loops at alternate 10 m, 13 m and 10 m heights, with these loops spaced 50 m apart, and the total length is 4.8 km. Figure 1 shows the flight path and the 200 blind nodes. The simulation is run for 40 iterations to determine the median error for all blind nodes. A minimum of 4 anchors are required for localization. The localization error and the number of generations will be examined. Starting with 200 blind nodes, the density of blind nodes will be increased until full localization can be obtained.

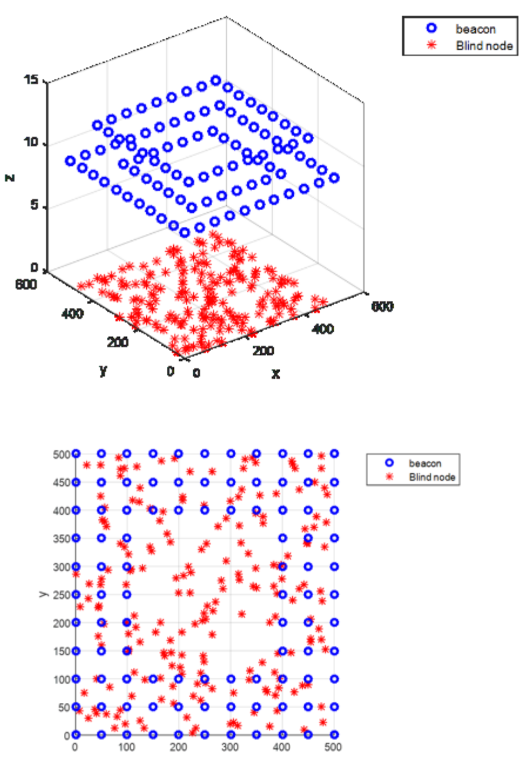

Figure 1: Localization using 50 m spacing between beacons using 200 blind nodes and edge path planning.

4.0 RESULTS

Using edge path planning, many blind nodes around the edge of the area are localized by the mobile anchor during first generation (G1) and the rest of the nodes around the edges are localized in second generation (G2). However, there are insufficient local anchors (and no mobile anchors) for blind nodes in the central region to be localized. The few central nodes that are localized have very high errors. Figure 2 shows the localization errors for each of the nodes, and Figure 3 shows the generations, including the large unlocalized central region. Those nodes located in the center of the sensing region could not be localized due to receiving less than 4 anchor positions.

The edge path planning which use 6 anchor positions to localize 200 blind nodes, produces higher error during the first generation (G1) for some of the blind nodes. While the nodes localized during the second generation (G2) also have higher error with the maximum of 57 m for node 207, 418, 0 due to weak RSSI which reached the maximum sensitivity of -90.5 dB. Blind node 31 (384, 264, 0) also has high error due to the error produced by the local anchor of 430,245, 0 and 410, 307, 0 as stated in the Figure 2.

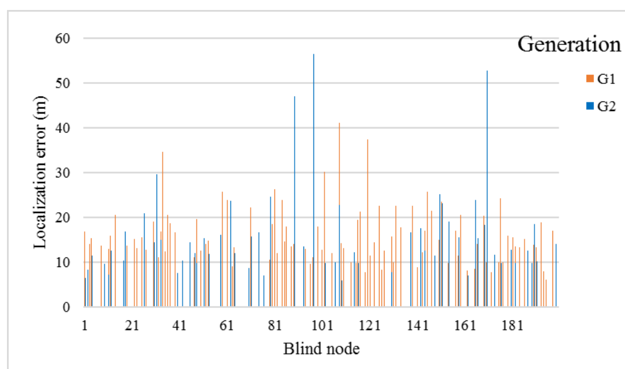

Figure 2: Localization error for 200 blind nodes based on generations using edge path planning.

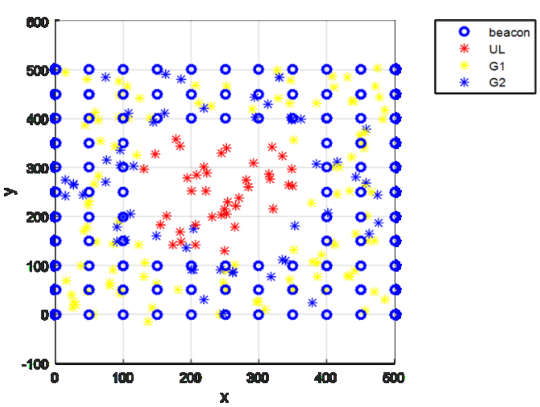

Figure 3:Localized and unlocalized (UL) nodes through generation (G1-G2) for 200 blind nodes using edge path planning.

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4.1 Results for 1000 Blind Nodes.

As shown in Figure 3, there were many blind nodes located in the center of the sensing region that could not be localized using the edge path planning. This is because there was an insufficient density of local anchors to propagate localization into this region.

Therefore, additional blind nodes are added to increase the chances of localization by local anchors. For 500 nodes, full localization was still not possible. The number of blind nodes is increased to 1000 nodes as shown in Figure 4. For this very large simulation, faster Deterministic Multilateration (DML) [3] localization was used to reduce the very long simulation time (remembering that the whole simulation is run 40 times to get stable statistics).

With this setup, all blind nodes are fully localized after the fourth generation as in Figure 5.

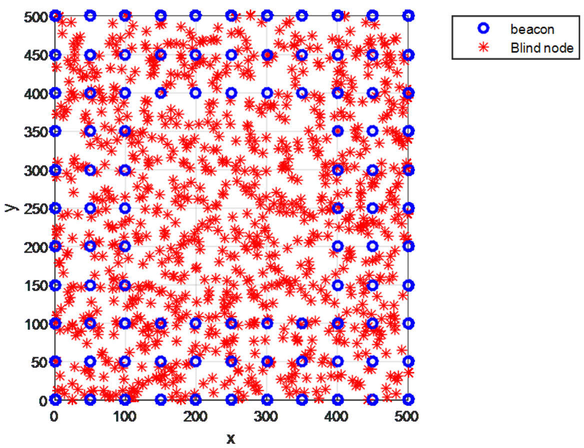

Figure 4: Localization for 1000 blind nodes using edge path planning.

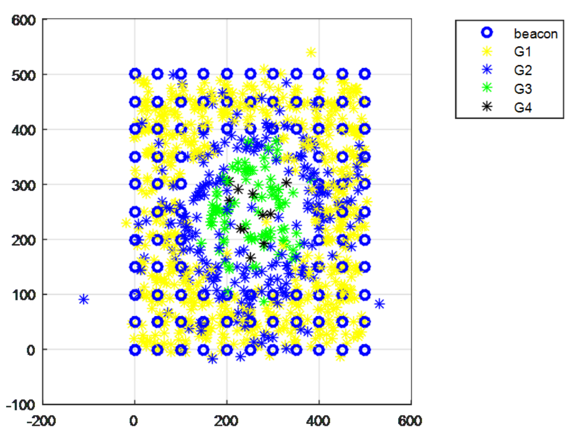

Figure 5: Localized blind nodes through generation (G1-G4) for 200 blind nodes using edge path planning.

The key result in this section is not the localization error since DML was used, rather than VPML, errors are not exactly comparable, and so have not been listed. Instead, the key result for this scenario is that a node density of around 4000 nodes per square km is needed to be able to do edge-based localization (experiments were conducted based on every thousands of nodes) . On the other hand, for a 500 m x 500 m area, this edge-based path only reduces the total path length from 5.5 km to 4.8 km, which is an insignificant saving.

For this scenario, a 4000 node per square km density is impractical (based on our simulation as stated in the above paragraph), and edge-based localization is not recommended for this particular scenario. Therefore, the square grid path planning could be suggested to improve the localization error.

5.0 DISCUSSION

Edge-based path planning can use localize a ring around the edge of the sensing area, but in order for this localization to propagate into a central area with no mobile beacon messages, an impractically high node density is required.

All these results are specific to this particular scenario, and radio range characteristics, and the results do not transfer to general guidelines. Rather, the key contribution is that such simulation studies can provide relatively quick decisions about operational requirements for the use of a mobile anchor prior to deployment.

6.0 CONCLUSION

Edge-based path planning was less successful due to higher node density (4000 nodes per square km) and 4 generations were required to fulfill the localization. Therefore, another experiment using the square grid path planning will be conducted for our future improvement.

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