Three-Dimensional Path Planning Model for Mobile Anchor-Assisted Localization in Wireless Sensor Networks

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Abstract—An extensive body of research has been accumulated on finding alternative methods for supplying nodes with their locations in Wireless Sensor Networks (WSNs). Although some path planning models in two-dimensional (2D) regions have been proposed in recent years, many WSNs’ realistic applications are applied in three-dimensional (3D) regions. In this paper, we introduce a three-dimensional path planning model for mobile anchor-assisted localization in WSNs. Our proposed model offers higher performance in terms of localization accuracy with a lower error rate in comparison to other proposed models.

I. INTRODUCTION

Localization is a fundamental need in many applications in Wireless Sensor Networks (WSNs) [1]. For example, tracking applications are highly dependent on the location of the nodes, such that it is very difficult to work without knowing the location of each entity [2]. Moreover, localization can improve energy efficiency, especially in models that depend on location-based routing techniques [2]. Several techniques are available to obtain sensor nodes’ locations. One of the simplest ways is to use Global Positioning System (GPS) devices. However, attaching a GPS device to each sensor node is impractical due to their cost and their limitations in some applications (e.g. indoor applications) [1]. On the other hand, other non-GPS techniques are proposed and can generally be categorized into two types, hardware dependent-techniques and topology-dependent techniques [1], [3]. In the hardware-dependent techniques, some information, such as signal strength, can help to localize sensor nodes. In the topology-dependent techniques, a set of ‘seed’ nodes with known locations are used to help determine the regular nodes’ locations [3]. Research is increasingly showing that integrating mobility in the WSN localization process can provide useful information and more accurate estimation [2], [4], [5]. A large number of studies on localization in WSNs have been proposed; however, those studies focus on two-dimensional (2D) areas. In most real-world applications, sensor nodes are deployed on planar surfaces where three-dimensional (3D) areas are found [6], [7]. Examples of these surfaces include indoor applications, such as floors, walls, tables and doors, and outdoor applications such as mountains, valleys, hills, and forests [6], [7]. Similar to [8], some of the potential applications of our proposed model can be shown as other sensor network tasks. For example, our model can be used to draw a map of the nodes’ location to help in 3D geographic routing or to enhance network connectivity by providing nodes with their neighbours’ locations.

In this study, we propose a new path planning model for mobile anchor-assisted localization in WSNs where nodes deployment occurs in 3D areas. Our proposed static model shows higher localization estimation accuracy, and thus lower localization error in comparison to other similar models. The rest of this work is organized as follows; in section II, we provide an overview of localization in WSNs with a brief discussion of currently existing works. Section III presents the network model and assumptions, while section IV shows our proposed model. Section V shows in detail the performance evaluation and the results. Finally, section VI includes future work and the conclusion.

II. RELATED WORK

In ordinary WSNs’ localization techniques, a set of static location-aware nodes, (called anchors, beacons, etc.) are distributed around the network to provide their location to the location-unaware sensor nodes, called unknown nodes, in their transmission range and to assist them to compute and estimate their location according to a specifically designed algorithm [1], [2]. The larger the network, the more anchors are needed.
However, the use of these stationary anchors comes with many challenges in cost, energy, and accuracy. Instead, a promising method to localize unknown nodes is to use a mobile anchor equipped with a GPS unit moving among unknown nodes and periodically broadcasting its current location (anchor point) to help nearby unknown nodes with localization. This approach can be effective in terms of cost and energy consumption [2]. The mobility approach in WSNs can use one of three approaches: random, dynamic or static. Static path planning is done prior to the localization and cannot be modified during the localization. Most static algorithms use the concept of the trilateration path for the mobile anchor to minimize localization errors and improve localization accuracy [9]. However, in real-life scenarios, the concept of quadrilateration is vital [6]. The quadrilateration method uses distance measurements from four different non-collinear nodes to localize other nodes in 3D space. Using the quadrilateration method will overcome the collinearity problem, where a set of nodes lie on the same straight line [6]. Reference [7] proposed two models, Layered-SCAN and 3D-Hilbert. SCAN and Hilbert are static models that were first proposed to work in 2D regions in [10]. Simply, in SCAN the mobile anchor can move in straight lines in one direction (x, or y) only. When the mobile anchor reaches the border of the area, it makes a U-turn to go back to the reverse side. It keeps moving in the same approach until reaching the last point. The mobile anchor stops frequently at fixed distances to provide its node neighbors that are located within its communication range with its current location. In the Layered-SCAN, the procedure is similar; however, it is applicable in a 3D area. Three coordinates (x, y and z) are considered where z represents a set of a 2D SCAN. Each 2D SCAN is called a layer. The distance between layers is the same as the distance between each two points in the 2D SCAN. Hilbert was an improvement of SCAN that allows the mobile anchor to make turns to avoid collinearity. In 3D-Hilbert, a similar concept is derived, but with more complexity as more points are needed to localize a node in a 3D area. A Random Waypoint (RWP) model is used in evaluation. Reference [4], presents a four-mobile-beacon assisted weighted centroid localization method in three-dimensional space. It suggests using more than a single mobile anchor for localization assistance. It also evaluates both 3D-RWP and Layered-SCAN using three different localization techniques.

III. NETWORK MODEL AND ASSUMPTIONS

The network area is represented as a three-dimensional field with a side length, S in m. A uniformly distributed set of unknown nodes, N, are spread around the network. Initially, sensor nodes are not location aware. Unknown nodes are assumed to remain static and do not change their location after the first distribution. Each network contains a fixed number of anchors, M. All anchors can determine their location within the network area. Each mobile anchor is able to move freely, in straight lines, in any direction in the network following its path model. For simplicity, we assume that the network area does not contain obstacles that could restrict anchor mobility. Unknown nodes and anchors can connect to each other only if they are located within the same transmission range, $R_{TX}$. Unknown nodes cannot share anchor locations with each other. Mobile anchors stop frequently within a fixed distance between each two points, defined as $d_m$. Mobile anchors are not energy constrained.

![Fig. 1: The proposed mobile path model in (a) one layer, and (b) full layers](image)
IV. THREE-DIMENSIONAL PATH PLANNING MODELS FOR MOBILE ANCHOR-ASSISTED LOCALIZATION

This work is intended to design a 3D path planning model for mobility-assisted localization in WSNs. The concept of this work is derived from the 2D path planning for mobile anchor-assisted localization in [11]. Our model consists of several layers \( L \) equals to

\[
L = \frac{S}{d_m} \quad (1)
\]

where \( S \) is the side length of the network and \( d_m \) is the distance between each two points (or layers). To overcome the problem of collinearity, we propose our model to let the mobile anchor follow an H-shape with a winding path each time. In 2D scenarios, at least three different points are needed to estimate a node’s location; however, in 3D scenarios, at least four points are needed for the estimation. Figure 1 shows the proposed model in one layer as in Figure 1a and full layers as in Figure 1b. For a better representation, we extend the distance between layers to be \( 2d_m \) in Figure 1. The proposed model works in three simple stages: the mobility movement stage, the localization information exchange stage, and the localization estimation stage.

A. Mobility movement

In this stage, the mobile anchor leaves the starting point at a corner of the network and moves in one direction, say \( y – coordinate \). In each step, the mobile anchor will make one movement with a travelling distance \( d_m \). The value of \( d_m \) remains fixed all the time. After this step, the mobile anchor will make another turn toward another direction, say \( x – coordinate \). The same procedure will be repeated until reaching the border of the network, which means a row of points is completed. It is then time for another row, and so the mobile anchor will take a step to form another row, toward the \( y – coordinate \) in this example. The mobile anchor will go back in the reverse direction of \( x – coordinate \), however, it will take \( 0.5 \times d_m \) only; this is important to prevent the points from being collinear. The same movement will be repeated until reaching the last corner of the deployment area. Here, the mobile anchor will move to form another layer by increasing the third coordinate, \( z – coordinate \), by 1. The movement will be taken in the reverse direction until reaching the starting point of the \( x \) and \( y – coordinates \) with the current \( z – coordinate \). The same procedure will be done until reaching a set of layers that is equal to \( L \).

B. Information Exchange

In 2D scenarios, when three different points are known, the unknown node can estimate its own location [11]. However, in 3D environments, the unknown node can estimate its location when four different points are reached. Thus, in each movement, the unknown node in the communication range of the mobile anchor exchanges the location information, stores it, and waits for the next localization information.

C. Localization estimation

As mentioned above, once four different localization messages are received by an unknown node, it can start estimating its own location in accordance to the localization technique used.

The procedure is summarized in the following algorithm.

**Algorithm 1 MA movement and UNode localization**

1: **procedure** NODE LOCALIZATION
2:  Nodes deployment
3:  MA movement
4:  UNode receives localization message
5:  if ReceivedMessages < 4 then
6:     UNode keeps waiting
7:     go back to 3
8:  end if
9:  Localization estimation
10: if MA movement \( \neq \) lastpoint then
11:     go back to 4
12: end if
13: Movement ends
14: Localization done
15: **end procedure**

V. PERFORMANCE SETTING AND EVALUATION

A. Performance Setting

To evaluate the performance of our proposed model, we implemented it along with three other models: 3D-RWP, layered-SCAN, and 3D-Hilbert. For fair comparison, two localization techniques were used: the weighted centroid localization (WCL) algorithm [12] and the Weight-Compensated Weighted Centroid Localization (WCWCL) algorithm [13].

For simulation, we used the Matlab environment with 50 run times. A set of 250 unknown nodes, \( N \), is assumed to be deployed in a 3D area with a side length, \( S \), of \( 100 \times 100 \times 100 \) m. A single mobile anchor, \( M \), is used to traverse the network and exchanges its location with other nodes. Different resolution values, \( R \), are used. The resolution value, \( R \), represents the relation between the communication range, \( R_{Tx} \) and the distance between every two points, the \( d_m \) of each path. It can be derived as

\[
R = \frac{R_{Tx}}{d_m} \quad (2)
\]

We used a realistic wireless channel by applying the specifications of a wireless node equipped with a
Chipcon CC1100 radio module [14]. The rest of the parameters are shown in Table I. The simulation tool and parameters were chosen to be consistent with other similar works.

**TABLE I: Simulation Parameters**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Side Length (m)</td>
<td>S</td>
<td>100</td>
</tr>
<tr>
<td>Number of Mobile Anchors</td>
<td>M</td>
<td>1</td>
</tr>
<tr>
<td>Number of unknown nodes</td>
<td>N</td>
<td>250</td>
</tr>
<tr>
<td>Resolutions</td>
<td>R</td>
<td>0.5, 0.75, 1, 1.25, 1.5, 2</td>
</tr>
<tr>
<td>Path Loss Exponent</td>
<td>( \beta )</td>
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</tr>
<tr>
<td>Power Loss at ( d_0 )</td>
<td>PL( d_0 )</td>
<td>-60</td>
</tr>
<tr>
<td>Reference Point</td>
<td>( d_0 )</td>
<td>1</td>
</tr>
<tr>
<td>Standard Deviation of Noise</td>
<td>( \sigma )</td>
<td>3</td>
</tr>
<tr>
<td>Simulation Run</td>
<td></td>
<td>50</td>
</tr>
</tbody>
</table>

B. Evaluation Results

We evaluate the path planning model’s performance in two metrics: the average localization error, and the standard deviation errors. All results are based on the average of the simulation run, 50 times.

1) Average Localization Error: Average localization error is an important metric that measures the accuracy of both the path planning model and the localization technique. The node localization error is estimated as

\[
\text{error}(i) = \sqrt{(x_i - u_i)^2 + (y_i - v_i)^2 + (z_i - w_i)^2}
\]  

(3)

Where \((x_i, y_i, z_i)\) are the real coordinates of the node \(i\), and \((u_i, v_i, w_i)\) are the estimated coordinates of the same node \(i\).

Hence, the average localization error, \(\text{error}_{\text{avg}}\), for the total number of unknown nodes, \(N\), is calculated as:

\[
\text{error}_{\text{avg}} = \frac{\sum_{i=1}^{N} \text{error}(i)}{N}
\]  

(4)

Figure 2a shows the average localization errors and the corresponding resolutions in all models when WCL is used. All path models offer close localization errors between 4 and 5 m when \(R = 0.5\); however, this distinction between the different models increases when the resolution increases. Our proposed model offers lower localization error when \(R = 0.75\) to 2. Our model guarantees that all nodes can receive the localization information and can solve the collinearity problem. The nature of movement in RWP increases the localization error in 3D-RWP since there is no guarantee that all nodes can receive the localization information. Layered-SCAN and 3D-Hilbert perform similarly to the ones in WCL, but with lower errors.

2) Standard Deviation of the Localization Error: The standard deviation of the localization error indicates how close values are to the average error. The standard
deviation of the localization error rate is calculated as

\[
\text{error}_{\text{std}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\text{error}_{(i)} - \text{error}_{\text{avg}})^2}
\] (5)

Where \( N \) is the number of unknown nodes, \( \text{error}_{(i)} \) is the localization error for node \( i \), and \( \text{error}_{\text{avg}} \) is the average localization error. Figures 2a and 2b show the average standard deviation errors and the corresponding resolutions in all models in which WCL and WCWCL are used. In both localization techniques, our model provides the lowest standard deviation values, which indicates that they are closer to the average. Indeed, in WCWCL, our proposed model shows an efficient performance with a standard deviation of 0.5 m only.

VI. FUTURE WORK AND CONCLUSION

In this paper, we presented our proposed 3D path planning model for mobile anchor-assisted localization in WSNs. Our proposed model shows lower localization error than some existing works, and thus has higher accurate estimation. For future works, we will extend our work to evaluate more of the current 2D models by testing their ability to work in 3D environments. Moreover, more evaluation perspectives will be added, including precision, localization ratio, energy consumption and path length.

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REFERENCES