An Area-Restriction Based Localization Method for Wireless Sensor Networks Using a Mobile Anchor

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Abstract—Localization is a very important issue to wireless sensor networks. The sensor node requires accurate location information in order to achieve the purpose of real-time monitoring and transmission of information. The more the sensor nodes and GPS modules are used in localization, the higher the localization accuracy can achieve, but employing more sensor nodes also leads to high costs. Thus, how to improve the localization accuracy while solving the problem of high costs has garnered attention. In this paper, an area-restriction based localization (ARBL) algorithm is proposed. The ARBL algorithm uses both range-based and range-free schemes, which combines area restriction setting and the sampling points from Monte Carlo localization (MCL) to improve the localization accuracy. The simulation results show that the ARBL algorithm proposed in this paper outperforms DuRT, MMRL and RL algorithms that employ a mobile anchor node, regardless of the number of the sensor nodes and the moving speed of the anchor node.

Keywords—localization; WSN; mobile anchor;

I. INTRODUCTION

A wireless sensor network (WSN), often used by Internet of things (IoT), has been widely adopted by target tracking, person tracking, monitoring \cite{1}, healthcare, agriculture, disasters, and environment management \cite{2} due to its advantages of low costs and easy deployment. Recent WSN research has been focused on localization.

In localization studies, the simplest way to obtain the coordinates of sensor nodes is to equip each sensor node with a GPS device. However, this will increase the power consumption of the network as well as the hardware costs associated with the use of GPS devices, and clearly contradict the basic concept of a WSN that employs cheap sensors and operate under an environment with limited power resources.

There are two types of localization approaches for WSNs: “range-based”\cite{3} and “range-free”\cite{4}. A range-based approach involves equipping each sensor with expensive hardware. To overcome the limitation of the range-based approach, range-free approaches which can be further classified into fixed and mobile anchor techniques are proposed. The common challenge of fixed anchor techniques is that the accuracy of locating each sensor highly depends on the number of fixed anchors. Using more fixed anchors would yield higher localization accuracy, but it also increases the hardware costs.

In practice, a wireless signal is strongly affected by factors such as multipath, diffraction, obstacles, and the direction of antennas. These factors add more noise to the Received Signal Strength Indicator (RSSI)\cite{5}, and location error becomes very apparent. Previous studies have proposed different methods to overcome such a limitation, such as increasing the number of the anchors and using RSSI algorithms. A review of these methods is presented in the section of related work.

The goal of this paper is to reduce the number of anchor nodes while improve the localization accuracy. An area restriction-based localization scheme, called ARBL, is proposed in this study. The proposed ARBL uses area restriction setting and the sampling points from Monte Carlo localization (MCL) to improve the localization accuracy. The remainder of the paper is organized as follows. Related work is described and summarized in section II. The scheme proposed by this paper is discussed in section III. The simulation results used to verify the proposed scheme are presented in section IV. Finally, the conclusions are drawn in section V.

II. RELATE WORK

It is common to divide the mobile localization approaches into two categories: employing mobile sensors and mobile anchors. The mobile-sensor methods, such as the particle swarm optimization (PSO)\cite{6}\cite{7} and the MCL\cite{8}, moves sensors to detect sensor node location. But to improve the localization accuracy it requires to deploy more nodes, leading to higher hardware costs. To cut back the costs, more and more anchor localization algorithms have been proposed over the years. Ssu et al., for example, proposed a range-free localization scheme using mobile anchor points\cite{9}. Each anchor was equipped with a GPS module, moved in a sensing field and broadcast its current location periodically. The sensor nodes obtained the RSSI information and the coordinates of sensors and estimated their locations. With this scheme, no extra hardware or data communication was needed. The localization scheme was inspired by the perpendicular bisector of a chord conjecture. The conjecture described that the perpendicular bisector of any chord passed through the center of the circle. As shown in Fig. 1, $S$, which is the center of the circle, is a sensor node, and the communication radius $R$ constitutes a circle. The circle and the two points moving
anchor nodes. The two points represented by the sensing nodes at the first point and the last point will ideally be on the circle and form a string (\( AB \)). By using mathematical geometry, the middle of the AB will pass through the point that represents the sensing node. The sensing node will then be located on the vertical line. However, the actual location of the sensing node cannot be identified, if we only known that there is a relationship between the sensing node and the midline. A theorem that lies in the center of the same circle is therefore used to estimate the location of the sensing node.

![Fig. 1 localization method proposed by Ssu et al [9].](image)

The localization method proposed by Ssu et al. is susceptible to the boundary effects, DOI and other issues, resulting in lower localization accuracy. Therefore, some studies proposed to use methods in conjunction with the RSSI localization method, but RSSI[10] is also susceptible to environmental disturbances, such as refraction, diffraction, and scattering. Thus, Zhang et al. proposed a mobile maximum rectangle localization scheme, called MMRL[11]. This localization algorithm differed from the above mentioned algorithms because MMRL did not have to rely on other measurement information such as angles, distances and received signal strength, so MMRL were not subject to environmental interference caused by signal fluctuations that decreased the localization accuracy.

The MMRL employed a mobile anchor node. The mobile anchor node moved around the sensing area and broadcast a beacon message. The sensor node then used the geometry technique to find the maximum rectangle which enclosed the node itself to obtain the location information, as show in Fig. 2.

![Fig. 2 Schematic of constructing the largest square.](image)

Moreover, an RSSI-based localization scheme, called “dual RSSI trend (DuRT) [12]” was proposed which used the relationship between the RSSI and the distance, to find an increasing and a decreasing trend of RSSI values for each trajectory of a mobile anchor. The DuRT was based on the PB localization algorithm, and it obtained a smoother RSSI curve by using the curve fitting technique, and the intersection of double trend polynomials after curve fitting was employed to find the projection point of the sensing node on the trajectory. The DuRT effectively overcame the problem of projection point offset due to RSSI fluctuations, so it could improve the localization accuracy.

The above mentioned localization algorithms all aim to improve localization, but they require that the anchor node to move toward the sensor node at least twice within the communication range, resulting in more time spent on the localization, and the successful localization rate is affected by mobile anchor nodes.

In this paper, a new method, called ARBL, is proposed, which decreases the influence of the boundary on the localization accuracy caused by the trajectory of anchor nodes by taking regional limitation and sampling points into consideration. Compared with other methods, the proposed method is not affected by the similarity of the trajectory of the anchor nodes or the scenario in which the anchor nodes are at the same side. Therefore, the method reduces the localization error. In addition, in an environment with obstacles, the method can also reduce the localization error resulted from trajectory changes caused by the obstacles.

III. THE ARBL METHOD

An area restriction based localization (ARBL) method is proposed in this paper. This method uses a mobile anchor node with a GPS module that moves in random directions [10]. When the anchor node moves within the communication range of a sensor node, the ARBL algorithm will estimate the location the sensor node by using the corresponding RSSI value calculated by the mathematical formula based on the two trajectories of the sensor node. A weighting system drawn from the MCL is also used to improve the localization accuracy. The ARBL algorithm is divided into four steps: curve-fitting, combining area restriction and samples, calculating the weight for a sampling point, and estimating the possible location based on double full trajectories. The following subsections provide the introduction of each step, and the overall flow chart of the algorithm is shown in Fig. 3.

A. Curve-fitting

In the localization method proposed in this paper, the projection point of the sensor node on the trajectory is obtained by curve fitting [12].

When an anchor node moves around the sensing field, it can receive two distinct trends of RSSI values along a straight line trajectory. This paper selects two maximum RSSI values (\( \text{RSSI}_{\text{max}} \) and \( \text{RSSI}_{\text{sec max}} \)) as the rising and downward trend of beacon points plotted against the reference distances. After that, the actual RSSI value is used to perform curve fitting, and \( p(x) \) and \( q(x) \) are the third-order polynomial rising and downward trend, respectively by equations (1) and (2), as show in Fig. 4.
Most mobile-anchor localization algorithms estimate the location of a sensor node by using the perpendicular bisectors of the sensor node. Such an approach is affected by the parallelism of the trajectory, resulting in a significant distance between the measured location and the actual location. This paper presents a regional limitation which is obtained by using different estimation methods to calculate the possible location of a sensor node. In the area restriction, an ARBL method is employed, which uses the sampling points in the MCL [9][12] to calculate the possible locations of the node. The MCL algorithm can be divided into the following four stages:

- **Initialization.**

  In this section, the sampling point range can be obtained by calculating the $\max_{\text{RSSI}}$, $\max_{\text{sec RSSI}}$ and communication disk of the sensor node. The range of sampling points can be expressed by equations (3) and (4). The range of area 2 is also calculated by equations (3) and (4)

  $\{x_{\min}, x_{\max}\} = \{\min (x_{\_ \text{Area}}), \max (x_{\_ \text{Area}})\}$

  $\{y_{\min}, y_{\max}\} = \{\min (y_{\_ \text{Area}}), \max (y_{\_ \text{Area}})\}$

  Where $\text{Area}_1$ is the set of coordinates for area 1, and $\text{Area}_2$ is the set of coordinates for area 2.

  After that, the range $(x_{\min}, x_{\max}, y_{\min}, y_{\max})$ can be obtained by using equations (3) and (4) to calculate the coordinates of n sampling points, as shown in the follows:

  $x_i = (x_{\max} - x_{\min}) \times \text{rand} + x_{\min}, \quad i = 1, 2, \ldots, n$

  $y_i = (y_{\max} - y_{\min}) \times \text{rand} + y_{\min}, \quad i = 1, 2, \ldots, n$

  where $n$ is the number of initialization sampling points, and rand is a random variable between [0,1].

  After calculating the coordinates of n sampling points by using equations (5) and (6), the set of the sampling points in area 1 and area 2 can be expressed by equations (7) and (8), respectively. The sampling points in the two areas are independent of each other, as shown in Fig. 5

  $S_{\text{Area}_1} = \{(x_1^1, y_1^1), \ldots, (x_n^1, y_n^1)\}$

  $S_{\text{Area}_2} = \{(x_1^2, y_1^2), \ldots, (x_n^2, y_n^2)\}$

  ![Fig. 3 The flow chart of the ARBL algorithm.](image)

  ![Fig. 4 Selection of top two RSSI values.](image)

  ![Fig. 5 Initialization- sampling points.](image)
• Prediction

In this phase, sensing nodes are static and the sampling points will the same at next time. In this approach, sampling points localization which is between the two regions are the same as initialization no matter what time change.

• Filtering

The process of sensor node localization is static; once the initial sampling point range is too large, the estimated location is deviated from the actual location. So this paper develops an area of filtering to remove sampling points way far away from the actual location of the sensor node to increase the accuracy of the sampling point location estimation. As shown in Fig. 6, when the initialized sampling point is outside the built-in triangular filtering area, it will be removed from the set of sampling points (s_{area1} and s_{area2}). The equations that determine the removal of a sampling point is given as:

\[ s_i^{'} | i = 1, 2, \ldots, n = \begin{cases} \bar{N} \times, \text{ if } s_i^{'} \text{ not in TRI} \\ s_i^{'} \text{, if } s_i^{'} \text{ in TRI} \end{cases} \quad (9) \]

\[ s_i^{'} | i = 1, 2, \ldots, n = \begin{cases} \bar{N} \times, \text{ if } s_i^{'} \text{ not in TRI} \\ s_i^{'} \text{, if } s_i^{'} \text{ in TRI} \end{cases} \quad (10) \]

Fig. 6 Filtering- sampling points.

• Re-filtering

The initial sampling range is used to regenerate new sampling points after removing the inappropriate sampling points in phase of filtering.

The resampling is then terminated until the number of sampling points in the filtering area meets the termination condition (n).

• Weighted sampling points

The MCL can successfully estimate the location of a sensor node within a sensing area, but using the average sampling points to find the location of the sensor node is likely to produce a larger error. To fix this problem, this paper uses projective geometry between the distance between the projection on the path of the node and the sampling points to calculate the weight of the sampling points.

• Projective geometry

The maximum RSSI/closest point is then calculated as the point of the intersection of p(x) and q(x). The reference distance of this point, D, is obtained by solving the following equation:

\[ p(x) - q(x) = 0 \quad (11) \]

from the beacon points (x_0, y_0) and (x_1, y_1), the slope of the anchor trajectory in (11) can be calculated, as shown in Fig. 7. Then, the coordinates of the maximum RSSI/closest point M is obtained and shown as follows:

\[ M = \frac{y_{AP1} - y_{AP0}}{x_{AP1} - x_{AP0}} \quad (12) \]

\[ x_{pre} = x_{AP0} + d \cos \theta \quad (13) \]

\[ y_{pre} = y_{AP0} - d \sin \theta \quad (14) \]

Fig. 7 The sensor node projected on the track.

C. Calculating the weight for a sampling point

The weight of a sampling point is the difference between the distance between a sampling point and its projection point, and the distance between the projection point and the location of the sensor node, and it can be presented as:

\[ w_i^{1} = \mu \frac{d \left( s_i^{1}, P \right)}{d_{pre}^{2}} , \quad i = 1, 2, \ldots, n \quad (15) \]

\[ w_i^{2} = \mu \frac{d \left( s_i^{2}, P \right)}{d_{pre}^{2}} , \quad i = 1, 2, \ldots, n \quad (16) \]

where \( w_i^{1} \) and \( w_i^{2} \) are the weight of area 1 and area 2, respectively.

D. Calculating the possible location

After the weight is normalized, the product sum of the sampling point and the weight can be obtained, and the possible position is calculated. The calculation is represented by the equations (17) to (20) and described in Fig. 8.

\[ x_{pre} = \sum_{i=1}^{n} \left( s_i^{1} \times w_i^{1} \right) \quad (17) \]
\[ y_{PP} = \sum_{i=1}^{n} (y_i^{1} \times w_{-nor}^{1}) \]  

(18)

\[ x_{PP} = \sum_{i=1}^{n} (x_i^{1} \times w_{-nor}^{1}) \]  

(19)

\[ y_{PP} = \sum_{i=1}^{n} (y_i^{2} \times w_{-nor}^{2}) \]  

(20)

where \((x_{PP1}, y_{PP1})\) and \((x_{PP2}, y_{PP2})\) are the possible location coordinates, respectively.

In order to avoid this situation, an ARBL algorithm is proposed in this paper, and the performance of the proposed ARBL algorithm is compared with the performance of other localization algorithms, such as DuRT [12], MMRL [11] and RL [13], in an obstacle-free environment. The number of sensor nodes, the speed of the anchor node and other parameters used in the simulation are listed in Table 1. The simulation software is MATLAB.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation area</td>
<td>(31 \times 31) (m²)</td>
</tr>
<tr>
<td>Radio range</td>
<td>10 (m)</td>
</tr>
<tr>
<td>Number of sensor nodes</td>
<td>100</td>
</tr>
<tr>
<td>Speed of the anchor node</td>
<td>1 (m/s)</td>
</tr>
<tr>
<td>Broadcasting of the anchor node</td>
<td>Every 1 (s)</td>
</tr>
<tr>
<td>Number of the samples</td>
<td>50</td>
</tr>
</tbody>
</table>

The localization error generated by using different methods in an obstacle-free environment is compared, and the results are shown in Fig. 10. In the comparison, the number of the sensing nodes used in the simulation is from 100 to 140, and the moving speed of the anchor node is from 0.2 to 1 m/s. The simulation results show that the average localization error of using DuRT increases when the number of the sensor nodes increases, because DuRT is easily affected by the boundary, which leads to incomplete or near-parallel trajectories, and the localization has to rely on the use of vertical intersection, so the deviation of the estimated actual location is large. Moreover, unlike the localization error slightly affected by the number of the sensor nodes when DuRT is employed, the number of the sensing nodes has no effect on the localization error when the ARBL algorithm is used.

When the moving speed of the anchor node decreases from 1 meter per second to 0.2 meter per second, the average localization error of using DuRT increases. The RSSI is susceptible to environmental interference, so when the interval
of the node receiving the information from the anchor node is reduced, the fluctuation becomes greater than the RSSI change between each beacon points, resulting in an increase in the localization error. By comparison, the localization error of using the ARBL algorithm proposed in this paper slightly decreases, when the moving speed of the anchor nodes decreases. This is because more sensor nodes can receive the information sent by the anchor node and the chance that the ARBL algorithm determine the type of trajectories as double full trajectories increases, so the localization error is slightly reduces, as shown in Fig. 11.

![Graph showing comparison of localization error](image)

**Fig. 11** Comparison of the localization error when the moving speed of the anchor node varies.

V. CONCLUSION

Based on the simulation results, the ARBL algorithm proposed in this paper outperforms other localization algorithms that employ a mobile anchor node, regardless of the number of the sensor nodes and the moving speed of the anchor node. In practice, however, localization might not be done in an ideal obstacle-free environment. In an environment with obstacles, it will be difficult to obtain double full trajectories. Rather, a single or incomplete trajectory might be detected. Thus, the future will focus on these types of trajectories using the proposed ARBL algorithm.

REFERENCES


