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SQUARE GRID PATH PLANNING FOR MOBILE ANCHOR-BASED LOCALIZATION IN WIRELESS SENSOR NETWORKS

Abstract *Localization is to provide all sensor nodes with their geographical positions. A mobile anchor-based localization in wireless sensor networks uses a mobile anchor equipped with GPS, which travels along a predetermined path. At each specified beacon point, it broadcasts its current known position to help other sensor nodes with unknown locations estimate their positions. This paper analyzes the determination of beacon points based on a square grid. We propose an improved path planning model named Union-curve. Our proposed model incorporates all beacon points of five previously developed paths, namely, SCAN, HILBERT, S-type, Z-curve, and Σ -Scan on the commonly used square grid decomposition of area. Unknown sensor nodes estimate their positions using two techniques, APT and WCWCL-RSSI. Simulation results show that the proposed model has higher accuracy, with a big difference in error rate compared to the other models. In addition, this model guarantees maximum coverage with less path resolution value.*

Keywords localization, mobile anchor, path planning model, wireless sensor network, square grid decomposition, beacon points

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1. Introduction

Sensors are inexpensive devices with built-in sensing, processing, radio communication functionality, and power components [33]. They transfer measured physical or environmental conditions such as temperature, sound, vibration, pressure, or even luminosity into an output signal that can be processed or displayed [37]. Many of them are deployed in a geographic area, called the region of interest (ROI), to create a wireless sensors network (WSN) that facilitates remote monitoring and control of the physical environment with greater precision. After deploying the sensor nodes, WSNs operate autonomously and are entirely transparent to the user. Besides, they can be self-configured and self-managed without human intervention. WSNs can have a wide variety of applications classified according to the nature of use in six categories: environment, military, industrial, flora and fauna, health, and urban [14, 25].

The data collected by the sensors are routed through multi-hop communications [33]. Therefore, the identification of the information source and computing the location of the event plays a primordial role in many WSN operations such as routing and data broadcasting schemes [27]. However, in some cases, due to dangerous or vast environments, it is difficult to locate the sensors manually, causing the problem of localization in WSNs. Using hardware solutions by installing a Global Positioning System (GPS) module for localization is expensive, especially for large-scale installation, despite the decrease in the cost of GPS receivers. Furthermore, the power consumption of GPS devices decreases the lifespan of sensor networks. Thus, several localization algorithms have been developed in the last decade to deal with this problem. The first WSN localization algorithms are based on a common idea of using a set of statically deployed nodes called landmarks (also known as anchors or Beacons) with known coordinates (nodes are equipped with GPS, for example) to transmit their coordinates to the other unknown sensors, to help them localize themselves [5, 9, 23, 24, 36, 45, 47].

Another promising idea has become possible, especially given the recent advances in mobile robot technology, in which all landmarks are replaced with a single mobile anchor node or a set of mobile anchor nodes. These mobile anchors are equipped with GPS units and move around the entire ROI to provide unknown sensor nodes with their locations [16, 40]. A comprehensive review of the recent literature describing mobile anchor node-assisted localization algorithms in WSNs was provided in [18]. In the area of research, the primary challenge is to identify an optimal path model for mobile anchors for locating unknown sensors in a WSN. As it is pointed out in [22, 48], the problem of path planning for mobile anchor nodes based WSNs localization is to design an efficient movement trajectory respecting three proprieties: (i) the trajectory should pass closely to as many potential node positions as possible to localize as many unknown nodes as possible, (ii) to obtain a unique estimation of the position of unknown nodes, the trajectory should be designed in such a way that all possible unknown nodes are fully covered by at least three noncollinear anchor points, and (iii) the trajectory should be as short as possible to save energy consumption of mobile

anchors and localization time.

Furthermore, the movement of the mobile anchor must be well planned to maximize the positions of the beacons which can give high localization precision [7]. In this context, most recent proposed models have only used three regular geometric shapes, namely, triangle, square, and hexagon to tessellate a two-dimensional plane as the basis for constructing routing paths [6]. Examples of such research include square grid decomposition [7,27,43,50], triangle grid decomposition [15,17,20,21,30] and the ones based on hexagonal grid decomposition can be found in [6,8,11,22]

The main contributions of this work are the design, implementation and evaluation of a path planning method for mobile anchor-based on square grid decomposition called Union-curve. The latter contains all beacon points of five trajectories, HILBERT, SCAN, S-type, Σ -Scan, and Z-curve, which maximize the number of beacon points. Among the advantages of Union-curve are offering good quality packets with a strong signal since it passes as closely to unknown node positions. It also provides coverage of the entire region of interest with a small resolution value as well as decreases energy consumption by minimizing the number of corners. Simulation results showed that the proposed model has higher accuracy with a lower error rate.

The rest of this paper is organized as follows. Section 2 presents the existing literature reviews proposed for localization in WSNs. Section 3 gives the background of the localization techniques used through the paper. Section 4 presents the proposed approach and describes the underlying model. Simulation environment and system parameters are provided in Section 5. Section 6 is devoted to simulation results and performance analysis. Finally, Section 7 concludes the work and proposes directions for future work.

2. Related works

The process of mobile anchor-based localization is based on two essential parts: path planning of the mobile anchor node and the localization algorithms.

2.1. Mobile anchor path planning

The choice of an optimal path of the mobile anchor is a complex problem. The authors of the paper [48] are the first authors who raised the problem of finding a good path planning and discussed it, but without offering any specific solution. In [18], path planning is classified into static and dynamic path planning. Since in this paper we are concerned with static paths, we provide the following a brief account on some distinguished static paths such as SCAN [27], HILBERT [27], Z-curve [43], Σ -Scan [50], and S-type [7].

In the SCAN path, the mobile anchor travels along the y -axis and the SCAN path degree is defined as the distance between two successive segments parallel to the y -axis. On the other hand, a level- n HILBERT space-filling curve is generated by dividing the ROI into 4^n squares of which the centers are connected with 4^n segments.

The resolution of the HILBERT curve (also known as the HILBERT path degree) corresponds to the length of each line segment. SCAN offers the best performance with a fine path degree, but with a coarse path degree, while HILBERT is the best choice since it solves the problem of collinearity posed by SCAN, but with an increase in the number of corners.

Another example of a space-filling curve is the Z-curve where a level- n Z-curve divides the ROI into 4^n squares and connects the centers of squares and the center of each basic curve via Z-shape. The square side length is the Z-curve path degree. This algorithm solves the collinearity problems, but it increases the number of corners. In parallel, the Z-curve decreases the path length and reduces the localization time. In [49], an algorithm with two mobile anchors instead of a single mobile anchor was proposed using the Z-curve trajectory.

The Σ -Scan curve is a cross between SCAN and Z-curve that benefits from both of their advantages. It has three kinds of units, namely Double-Unit, Square-Unit, and Triple-Unit. The latter can constitute an arbitrary rectangle to give the best exploitation of ROI compared to Hilbert and Z-curve, but it is relatively complex in its implementation. The unit side length represents the Σ -Scan path degree.

In S-type, the unknown nodes can receive four beacon messages in each sub-square area. Here, the mobile anchor displacement distance between two broadcast points represents the S-type path degree. This approach compared the trilateration with two generalized geometrical localization algorithms.

It is worth noting that after choosing the right path, one needs to set the most exact path parameters such as path degree, path movement, and path length in order to achieve the more accurate results [4].

2.2. Localization algorithms

The localization algorithms are classified into two categories: range-based and range-free localization algorithms [19]. The range-based localization algorithms use range information (geometry measurements) such as angle or distance between unknown sensor nodes to be located and mobile anchors. The distance is measured using material properties of communication signals such as Received Signal Strength Indicator (RSSI) [32], Time Difference of Arrival (TDoA) [46], and Angle of Arrival (AoA) [41]. Among the techniques used for calculating the location of unknown sensor nodes are trilateration [38], multilateration [35], and triangulation [29]. In this context, a more recent indoor localization algorithm called weighted three minimum distances method [13] was proposed to deal with the poor accuracy of distances estimated from RSSI. The latter are based on both multilateration and averaged RSSI values.

In contrast to the range-based localization algorithms, the range-free localization algorithms do not require distance or angle for localization but use only connectivity information between unknown sensors and beacons [43]. In general, range-based localization algorithms have higher positioning accuracy and complexity than range-free localization algorithms [13]. In [19], range-free localization approaches are grouped

into four distinct categories: connectivity localization algorithms [23, 36], centroid localization algorithms [3, 12], energy attenuation localization algorithms [42, 52], and region overlap localization algorithms [28, 31, 51].

The widespread adoption of wireless sensor network technologies in various fields has led to continuous research to improve localization techniques and achieves better localization performance. Recent studies have focused on the use of various artificial intelligence (AI) approaches to handle localization issues in WSNs. In [1], a solution for the dynamic formation of the mobile anchor path based on the flow direction algorithm metaheuristic approach was presented. Besides, the localization of unknown sensor nodes can be modeled as an optimization problem. In [10], an improved multiple-disturbance strategy grey wolf optimization algorithm was presented to estimate the locations of unknown sensor nodes in order to improve localization accuracy. A review and analysis of the literature on existing research trends of coverage, deployment and localization challenges using AI techniques for WSN enhancement can be found in [39].

3. Background on localization techniques

In this paper, we choose two different localization techniques for calculating unknown sensor locations, namely, Accuracy-Priority Trilateration (APT) technique [38] and the weighted centroid localization algorithm based on RSSI (WCWCL-RSSI) [12]. APT is a range-based localization algorithm, whereas WCWCL-RSSI is a range-free localization algorithm.

3.1. Accuracy-Priority Trilateration (APT)

Trilateration [38] is a mathematical method of determining the node's relative position in relation to three known position anchors. For this, it is necessary to determine precisely the distances between an unknown node and three anchors. In this work, we adopt the RSSI-based trilateration localization scheme where the distances are calculated using RSSI.

APT localizes unknown sensor nodes relying on three nearest received messages from the mobile beacon. This technique uses the three strongest RSSI values, which offers the possibility of estimating the location with higher accuracy. In [43, 50], APT technique gives very good results compared to the Time-Priority Trilateration (TPT) technique, which derives the position of the unknown sensors based on earlier received messages, as opposed to Cosine Rule based Localization (CRL) algorithm proposed in [44] shows superior performance compared to APT.

3.2. Weight-Compensated Weighted Centroid Localization Based on RSSI (WCWCL-RSSI)

WCWCL-RSSI is a weighted centroid localization algorithm based on RSSI proposed in [12], and depends on the idea of WCL [3]. In [2, 12, 26], among the centroid

localization algorithms tested, WCWCL-RSSI is the most accurate compared to WCL.

Let $a_i = (x_i, y_i)$ denotes the coordinate of an anchor node i and g represents the degree that determines the contribution of each anchor node. w_i represents the weight of anchor node a_i that depends on the distance between the anchor node i and the unknown node. The process of WCWCL-RSSI consists of three essential phases:

- i) When an unknown node receives the signals from different anchor nodes of which the size reaches from 1 to n anchor nodes ($i = 1 \dots n$), that is $n > 1$, it records the RSSI values and the coordinates of each anchor a_i .
- ii) Let w_i be the weight of anchor node i , the improved weight Wn_i is calculated as [12]:

$$Wn_i = \frac{W_i \cdot n^{2 \cdot W_i}}{\sum_{j=1}^n (W_j \cdot n^{2 \cdot W_j})} \quad (1)$$

where

$$W_i = \frac{w_i}{\sum_{j=1}^n w_j} = \frac{\sqrt{\left(10^{\frac{RSSI_i}{10}}\right)^g}}{\sum_{j=1}^n \sqrt{\left(10^{\frac{RSSI_j}{10}}\right)^g}} \quad (2)$$

- iii) Finally, the position of the unknown node is expressed as

$$P = \sum_{i=1}^n Wn_i \cdot a_i \quad (3)$$

Here, $P = (x_p, y_p)$ represents unknown node coordinates and $a_i = (x_i, y_i)$ represents the location of anchor i .

4. Proposed approach

In this section, we describe the main components of our proposed model for mobile anchor-based localization henceforth referred to as the Union-curve algorithm. It is composed of two main steps as depicted in Figure 1.

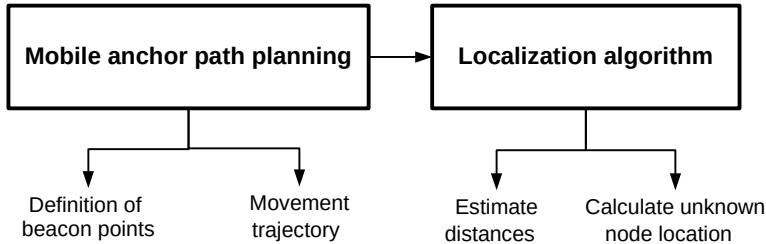


Figure 1. Union-curve algorithm.

The first one is to define the mobile anchor path planning and the second one is the localization algorithm. The following subsections will give more details about these two steps.

4.1. Mobile anchor path planning

In this phase, it is necessary to define a mobile anchor trajectory and when should beacon packets be broadcasted.

4.1.1. Position of beacon points based on square grid

We assumed that a WSN has been deployed in a two-dimensional $S \times S$ area. In the square grid decomposition, the ROI has been divided into squares as shown in Figure 2(a).

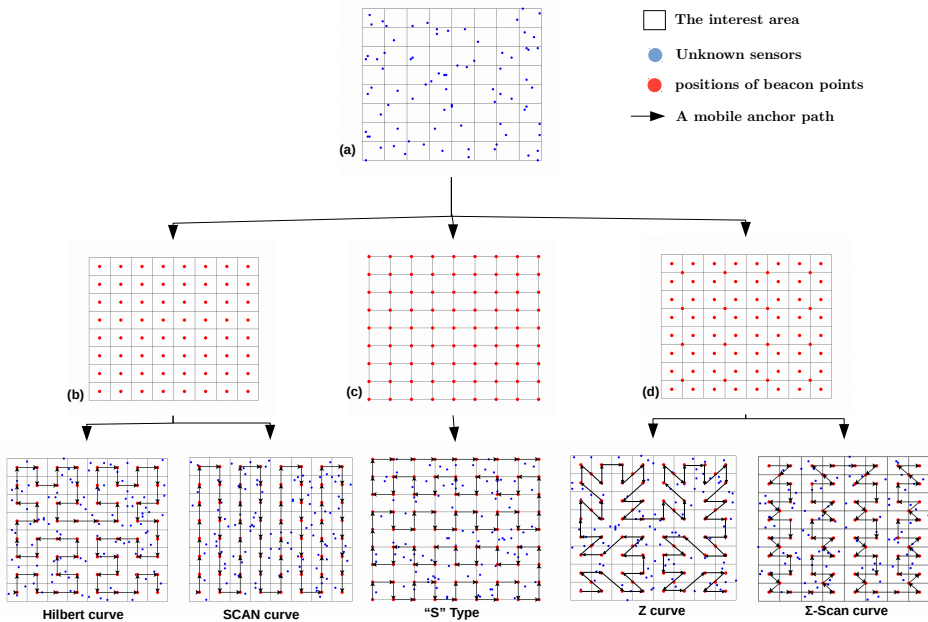


Figure 2. Decomposition of area and determination of positions of beacon points.

The side length of square L is adjusted according to the communication range r of the mobile anchor node and the ROI length S . The L value is the path degree. To help unknown sensor nodes to locate themselves with higher accuracy, it is necessary to find the best deployment of beacon points. Doing so, three possibilities based on the square grid decomposition are investigated to define the position of beacon points:

- The centers of squares are chosen as the points as beacon points as illustrated in Figure 2(b). This proposition was also adopted by both SCAN and HILBERT. In these two path plannings, the mobile anchor passes through the same broadcast points but not in the same order as shown in Figure 2.
- The vertices of squares are defined as beacon points as shown in Figure 2(c). The S-type also follows this idea as indicated in Figure 2.
- The centers of squares and the centroid points of each four sub-square are defined as beacon points as shown in Figure 2(d). Two path plannings adopted this proposition, namely, Z-curve and Σ -Scan. The Σ -Scan path presented in Figure 2 uses only Square-Unit. One should note that SCAN, HILBERT, Z-curve, and Σ -Scan passes through the same beacon points but not in the same order in the case of the two latter path plannings.

In our proposed path planning model Union-curve, the beacon points are deployed at both the centers and the vertices of squares as depicted in Figure 3. Union-curve contains more beacon points than the other five paths (HILBERT, SCAN, Z-curve, S-type, and Σ -Scan) as depicted in Figure 3. Therefore, it passes as close as possible to unknown node positions, so it offers good quality packets with a strong signal that increases precision [48]. In each sub-square, the unknown nodes can receive five beacon messages as shown in Figure 4, which guarantees that all unknown nodes are fully covered.

4.1.2. Movement trajectory

Union-curve is simple, easy to implement, and covers the area by diagonal scanning. At the initial stage, a mobile anchor node is deployed on the corner of the area. Afterward, it travels through the entire ROI following the Union-curve trajectory and broadcasts its current location with an interval of L when moving vertically or horizontally, and with an interval of $\frac{\sqrt{2}}{2} \times L$ when moving diagonally as shown in Figure 3. This movement trajectory minimizes the number of corners for efficient path planning [21]. The path length of the Union-curve is calculated by Equation (4).

$$length_{Union} = (4 \times S) + (\frac{\sqrt{2}}{L} \times S^2) \quad (4)$$

4.2. Localization algorithm

A mobile anchor-based localization algorithm is a distributed algorithm where the computation of unknown nodes' positions is distributed among the sensor nodes. In these algorithms, only the communication between the mobile anchor and unknown nodes is carried out, which consumes less energy. The network consists of a certain number of unknown nodes deployed randomly and uniformly over a sensing field where there are no obstacles and a single mobile anchor node. Moreover, two processes are carried out in parallel. One process is executed by the unknown node, and another is executed by the mobile anchor node.

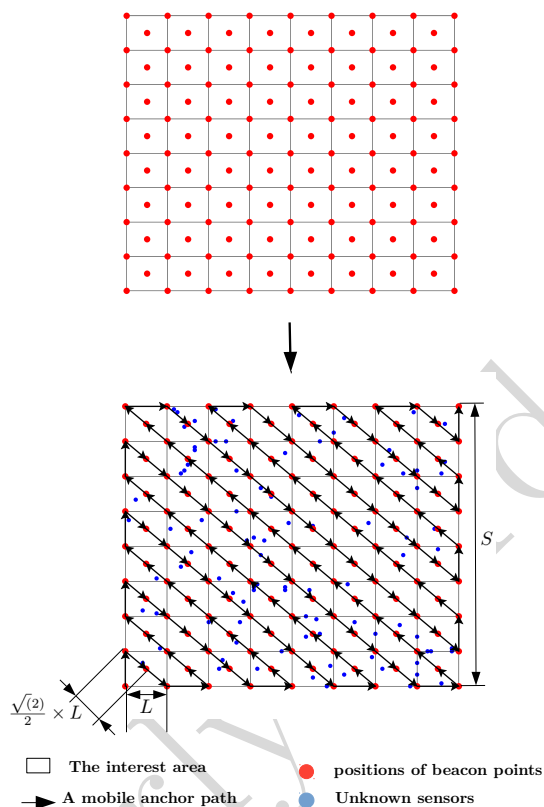


Figure 3. Union-curve.

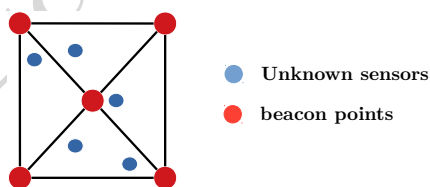


Figure 4. The sub-square in Union-curve.

4.2.1. The mobile anchor process

In the first stage, this process defines the path, configures the system parameters and determines the positions of the beacon points. Then, the mobile anchor travels along the ROI depending on a predefined trajectory. When it arrives at each beacon point, it broadcasts a packet containing its position. This process terminates when the

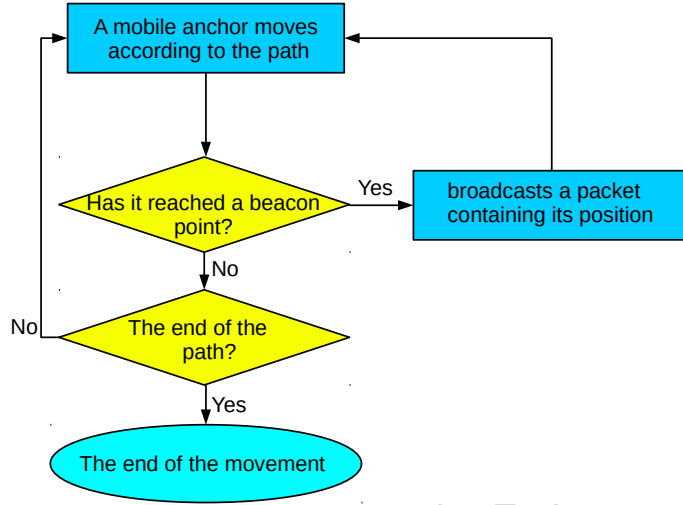


Figure 5. The mobile anchor process.

mobile anchor reaches the end of the path. The mobile anchor process is illustrated in Figure 5.

4.2.2. The unknown node process

In each beacon point, if the unknown sensor nodes are positioned in the coverage area of the mobile anchor, they receive a beacon packet and then calculate their positions using one of the localization techniques such as APT or WCWCL-RSSI.

The unknown node process with APT, presented in Figure 6, can be summarized in two steps. First, the unknown sensor node estimates the distance using RSSI once it receives a packet. Then, the unknown node keeps only the three no-collinear packets with the smallest distances and calculates its position using trilateration. The APT localization technique uses only the smallest distances and performs the collinearity test to accept a packet which consequently minimizes the collinearity problem.

The unknown node process with WCWCL-RSSI is presented in Figure 7. Each unknown node receives more than three different localization packets to calculate its position using WCWCL-RSSI. To test and improve the performance of WCWCL-RSSI method, we have implemented two tests.

1. The unknown node calculates its position based on the first 10 messages received and ignores the others.
2. The unknown node sorts the received packets according to the strongest signal and then calculates its position using the WCWCL-RSSI algorithm using a different number of ranked messages: first three, first four, and first five, respectively.

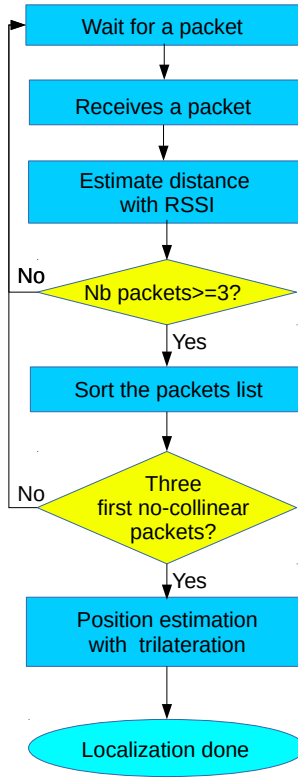


Figure 6. The unknown node process with APT method.

5. Simulation environment and parameters

Our proposed model was implemented using Python 3 programming language. A series of simulations have been conducted in order to analyze and evaluate its performance and the generated results were averaged over 50 run times.

For the wireless Channel model, we used realistic measured results reported in [34], The RSSI was measured using 2.4 GHz ZigBee wireless protocol based on XBee series 2 modules. The log-normal shadowing model was established for an outdoor environment. The simulation parameters are shown in Table 1.

6. Performance evaluation and simulation results

To analyze and evaluate the effectiveness of the proposed Union-curve model, five critical analysis metrics are used: average localization error, standard deviation of the localization error, localization ratio, energy consumption, and number of beacon points. These analysis metrics depend on two parameters namely the mobile anchor

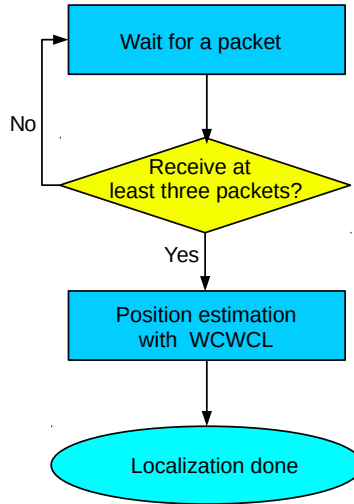


Figure 7. The unknown node process with WCWCL-RSSI method.

Table 1
Simulation parameters.

Parameters	Symbol	Value
Network size	S	$96\text{ m} \times 96\text{ m}$
Number of unknown nodes	N	100
Number of mobile anchors	M	1
Mobile anchor communication range	r	12, 24
Resolution	$R = r/L$	$3/4, 1, 5/4, 3/2, 7/4, 2, 9/4, 10/4$
Path loss exponent	γ	2
Standard deviation (dB)	σ	1.326
Reference distance (m)	d_0	1
Path loss at a distance d_0 (dBm)	PL_0	32
Transmitter power (dBm)	P_T	2
Distance under test (m)	d	1-100
Number of simulation runs	SR	50

communication range (r) and the path degree (L). Thus, the path resolution (R) is expressed as the ratio of r to L , that is, $R = r/L$.

6.1. Average localization error

The average localization error can be considered as the fundamental factor for evaluating the performance of any localization algorithms in WSNs. This value is calculated using Equation 5.

$$L_e = \frac{\sum_{i=1}^n Error(i)}{n} \quad (5)$$

where

$$Error(i) = \sqrt{(x_{ei} - x_i)^2 + (y_{ei} - y_i)^2} \quad (6)$$

In these equations, (x_{ei}, y_{ei}) and (x_i, y_i) represent the estimated and the real coordinates of the node i respectively, whereas L_e and n indicate the average localization error and the number of successfully localized nodes respectively. Remember that $n \leq N$ where N is the number of all unknown nodes.

Figure 8 depicts graphically a comparison in the average localization error for different resolution values between our model and the five other static path planning algorithms, namely Σ -Scan, Z-curve, SCAN, HILBERT, and S-type based on APT as a localization method. It is observed that the proposed Union-curve model has the highest accuracy with the lowest average error rate, followed by S-type, Σ -Scan, Z-curve, SCAN, and HILBERT. Moreover, when the resolution value exceeds 1.25, it becomes clear that there is a large difference in the error rate of about 0.26 between the Union-curve and S-type which comes second in terms of efficiency.

The results also show that each of the following pairs of curves (Σ -Scan, Z-curve) and (SCAN, HILBERT) have the same performance since the related mobile anchor passes through the same beacon points but in a different order. In addition to that, APT method focuses only on the smallest distances but not on the order in which messages are received.

As shown in Figure 8, all the curves stabilize separately after a certain resolution value, which means that at this value all the unknown nodes will receive the three messages that correspond to the three smallest distances. Thus, any increase in it will not affect the error rate and the results will remain unchanged since all messages that will be received by these unknown nodes are those sent by remote beacon points and are therefore not taken into account.

Furthermore, Union-curve achieves rapid convergence among them and remains stable on the same error rate of 0.3 after getting a resolution value equal to or greater than 1.0.

Figure 9(a) shows the average error ratio results obtained by these compared algorithms for different resolution values when applying the WCWCL-RSSI method with ten messages. As shown in the figure, Union-curves and S-type are the two best-performing path models each with the lowest error rate in 4 cases out of 8. Thus, they can achieve comparable performance in terms of average error rate. For the results in Figure 9(b), we have fixed the resolution value to 1.5 and varied the number of messages from 3 to 5, increasing it by one each time. Remember that WCWCL-RSSI algorithm bases its decisions on a certain number of received messages with the most significant RSSI values. Clearly, our model tends to derive the lower average error rate with a more accurate estimated location, especially when the number of messages equals 4. Similar to APT method, the curve of Σ -Scan coincides with those of Z-curve,

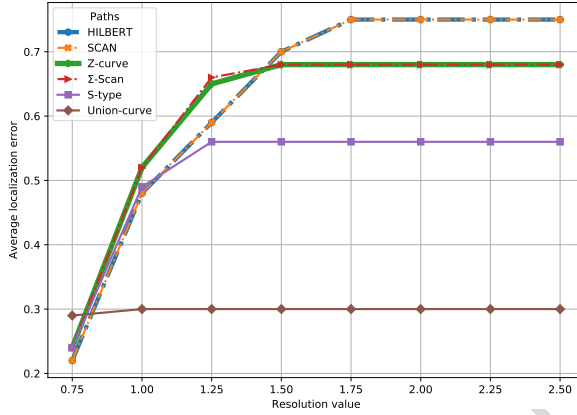


Figure 8. Comparison of average localization error rate based on APT method.

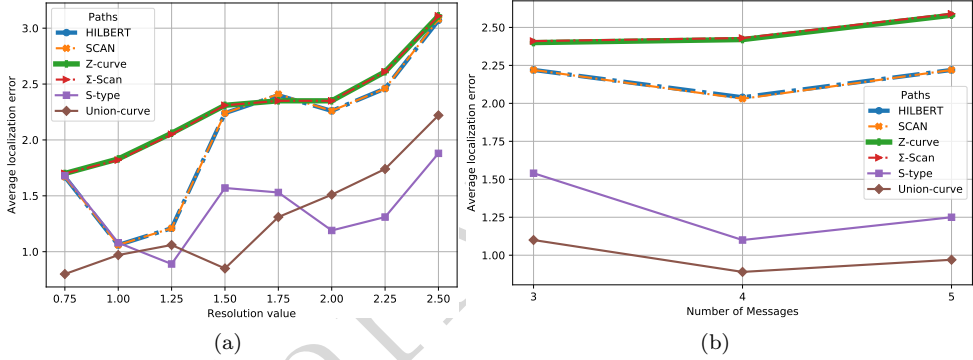


Figure 9. Average localization error with WCWCL-RSSI method.

and the curve of SCAN coincides with those of HILBERT since both pairs have the same beacon broadcast points.

6.2. Standard deviation of the localization error

The second analysis metric is the standard deviation of the average localization error. A low standard deviation indicates that most of the localization error values of unknown nodes are close to the average localization error. The standard deviation of the localization error rate std_{error} is calculated according to Equation (7).

$$std_{error} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Error(i) - L_e)^2} \quad (7)$$

where n , $error(i)$, and L_e are the number of localized nodes, the localization error for unknown node i and the average localization error respectively. The results obtained by applying the APT method are shown in Figure 10. The Union-curve has the lowest standard deviation values for this metric among all path models followed by S-type. This shows that the amount of dispersion around the average localization is less compared to the others. Moreover, note that when the path resolution increases, the standard deviation values increase until the localization ratio becomes 100% and hence reaches its stabilization point.

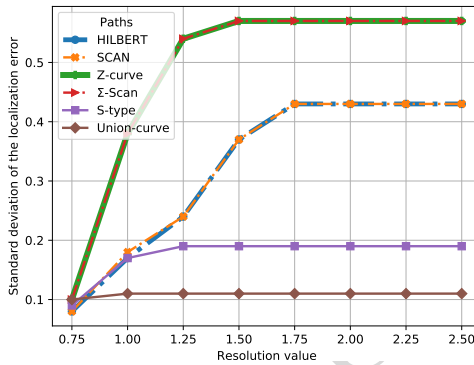


Figure 10. Standard deviation of the localization error with APT method.

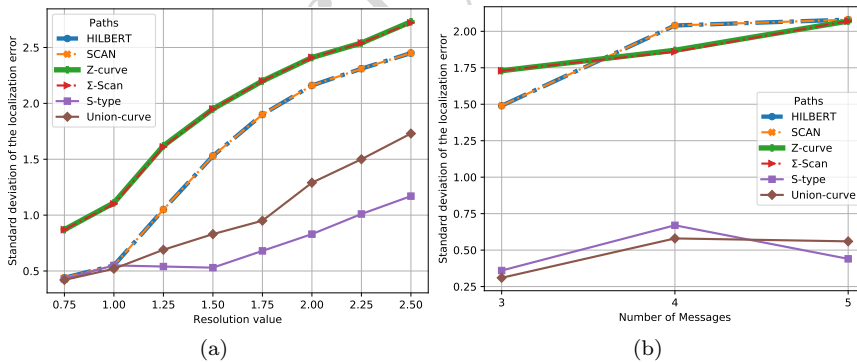


Figure 11. Standard deviation of the localization error with WCWCL-RSSI method.

The standard deviation of the localization error values for each approach based on the WCWCL-RSSI method with resolution value as a parameter is shown in Figure 11(a). Results show that there is a direct proportionality between the standard deviation of the localization error and the path resolution. This implies that an increase in the precision value leads to an increase in the standard deviation of the

localization error rate for all six paths but to a lesser extent for Union-curve and S-type. The standard deviation of the localization error values for each approach based on the WCWCL-RSSI method with a number of messages as a parameter is shown in Figure 11(b). Results reveal that Union-curve and S-type show the best performance compared to the other paths. In addition, our proposed path competes with the S-type curve path with a relatively small enhancement when the number of messages is 3 or 4.

6.3. Localization ratio

Another crucial performance metric is the localization ratio (coverage) which gives the proportion of sensor nodes that can be localized to total nodes. The goal of each path is to have a high number of localized nodes with a small value of the path resolution. The localization ratio can be computed as follows:

$$C_R = \frac{n}{N} \quad (8)$$

As explained previously, the terms n and N refer to the number of localized nodes and the number of all unknown nodes, respectively. The result of the analysis for all paths concerning the localization ratio is presented in Figure 12 and Figure 13 using APT and WCWCL-RSSI methods, respectively. It turns out that the two figures are almost identical and the localization ratio of each path with respect to the resolution value is the same when either applying APT or WCWCL-RSSI with a very slight exception in the case of SCAN and HILBERT paths. In addition, the resolution value greatly impacts the localization ratio and the resolution value increases all paths producing the same results for both methods. Let R denote the resolution value, Union-curve reaches a localization ratio of 100% (fully localized nodes) at $R = 1$, whereas at $R = 1.25$, $R = 1.5$, $R = 1.5$, $R = 1.75$ and $R = 1.75$ for S-type, Σ -Scan, Z-curve, SCAN, and HILBERT, respectively. Moreover, Union-curve can achieve a more than 90% localization ratio at only $R = 0.75$ whereas the others cannot even pass 40% of the localization ratio at this value.

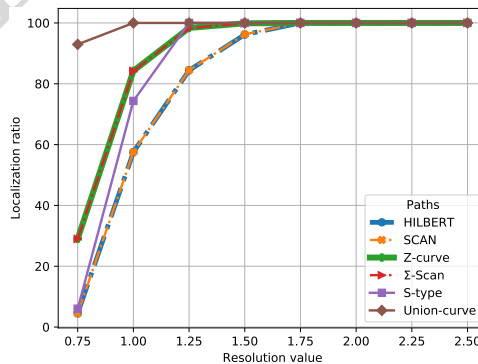


Figure 12. Localization ratio with APT method.

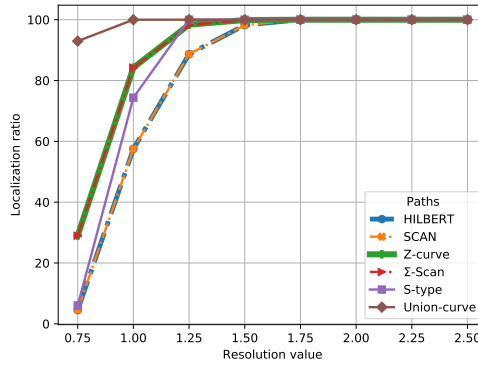


Figure 13. Localization ratio with WCWCL-RSSI method.

6.4. Energy consumption and number of beacon points

The calculation of the energy consumption is based on the average number of processed or received messages by the unknown nodes. Figure 14 shows that if the resolution value R increased, unknown nodes receive more messages to process.

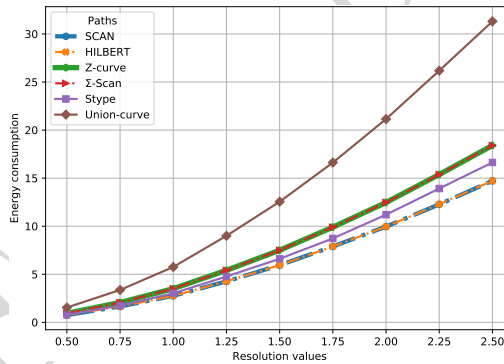


Figure 14. Energy consumption.

In fact, Union-curve has the highest average number of received messages. To minimize energy consumption, each unknown node takes into account during its calculations only the first ten received messages and ignores the others.

Table 2 compares the number of beacon points for the union-curve, SCAN, HILBERT, Z-curve, Σ -Scan and S-type curve. The number of beacon points depends on the size of the network S and the degree of path L (distance between each two beacon points). Note that the number of beacon points decreases when the value of L is increased. For example, in the case of Union-curve, when the value of L is doubled as shown in Figure 15, the number of beacon points decreases up to 41. The order o_b of HILBERT and Z-curve is calculated by Equation 9 with 4^{o_b} units squares.

Table 2
Number of beacon points.

Paths	Number of beacon points
SCAN(8*8 unit squares)	64
HILBERT(order 3)	64
Z-curve(order 3)	80
Σ -Scan(4*4 Square-Unit)	80
S-type (8*8 unit squares)	81
Union-curve (8*8 unit squares)	145
Union-curve with double L (4*4 unit squares)	41

For SCAN, S-type curve and Union-curve, there are $Nb_s * Nb_s$ units squares where Nb_s is computed by Equation 10. Table 2 indicates that Union-curve has more beacon points.

$$o_b = \log_2(S/L) \quad (9)$$

$$Nb_s = S/L \quad (10)$$

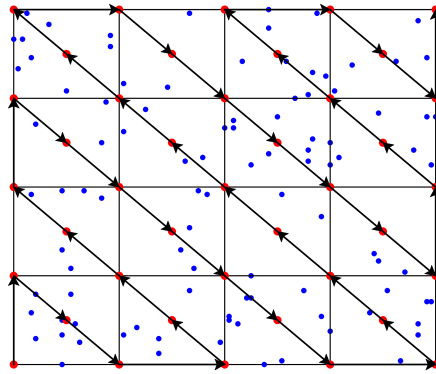


Figure 15. Union-curve with a double path degree L.

A smaller broadcast interval (path degree) indicates that the mobile anchor will broadcast its location more frequently [4], which improves localization performance but at the expense of relatively as demonstrated by the outputs depicted in Figure 16 and Figure 17. From these figures, it is seen that the obtained results are acceptable. However, the average and the standard deviation of the localization error are increasing compared to that in Figure 8, 9, 10 and 11 for all the methods used. In addition, the best results will be obtained by using either APT or WCWCL-RSSI methods with the number of messages used being four.

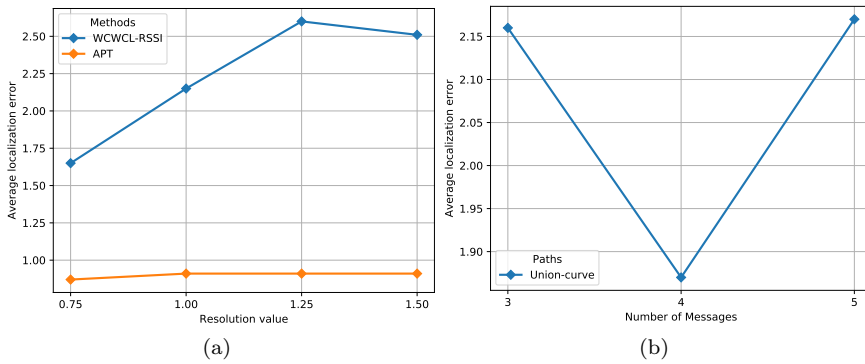


Figure 16. Average localization error of Union-curve with a double path degree L.

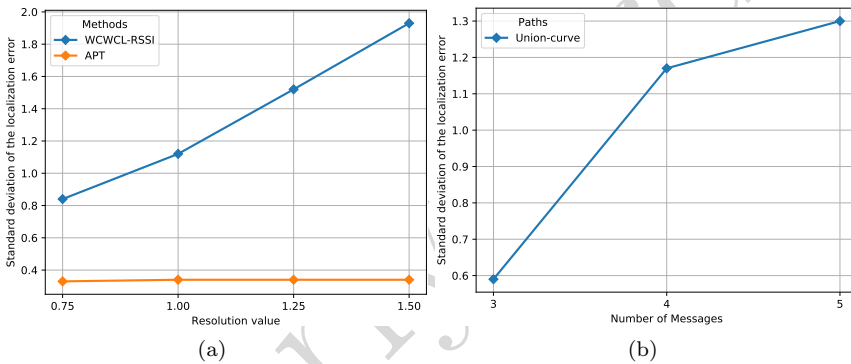


Figure 17. Standard deviation of the localization error of Union-curve with a double path degree L.

7. Conclusion

In this paper, we focus on the beacon broadcasting points regarding the square grid decomposition of the area. We propose the Union-curve path planning model that contains the union beacon points of five trajectories based on the square grid and minimizes the number of corners. The WCWCL-RSSI algorithm incorporated in our approach is tested using three different numbers of received packets with the strongest signal: the three best-ranked packets, the four best-ranked packets and the five best-ranked packets. The simulation results show that the proposed method achieves better or more competitive performance regarding localization accuracy compared to other well-known methods from literature, such as SCAN, HILBERT, Z-curve, Σ -Scan and S-type curve. Moreover, Union-curve with The WCWCL-RSSI algorithm produces better results when the number of received messages equals four. As future trends,

we plan to analyze other paths based on a triangular or hexagonal grid decomposition and deal with the obstacle-resistant mobile anchors in a given ROI.

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