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New Online DV-Hop Algorithm via Mobile Anchor for Wireless Sensor Network Localization

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Abstract: In many applications of Wireless Sensor Networks (WSNs), event detection is the main purpose of users. Moreover, determining where and when that event occurs is crucial; thus, the positions of nodes must be identified. Subsequently, in a range-free case, the Distance Vector-Hop (DV-Hop) heuristic is the commonly used localization algorithm because of its simplicity and low cost. The DV-Hop algorithm consists of a set of reference nodes, namely, anchors, to periodically broadcast their current positions and assist nearby unknown nodes during localization. Another potential solution includes the use of only one mobile anchor instead of these sets of anchors. This solution presents a new challenge in the localization of rang-free WSNs because of its favorable results and reduced cost. In this paper, we propose an analytical probabilistic model for multi-hop distance estimation between mobile anchor nodes and unknown nodes. We derive a non-linear analytic function that provides the relation between the hop counts and distance estimation. Moreover, based on the recursive least square algorithm, we present a new formulation of the original DV-Hop localization algorithm, namely, online DV-Hop localization, in WSNs. Finally, different scenarios of path planning and simulation results are conducted.

Key words: Wireless Sensor Networks (WSNs); mobile anchor; online localization; path planning

1 Introduction

Recent advances in the internet of things and Industry 4.0 have led to the emergence of a new trend in network structure, known as Wireless Sensor Networks (WSNs). Given their appearance, this type of wireless network has grown and attracted the interest of the research community and industrial applications. At present, WSNs have received considerable attention, and it has been used in many applications, such as security applications, object tracking for military applications, healthcare applications, and environmental applications[1–6]. This new technology has revolutionized the behavior and operation of several currently embedded system applications because of its miniature characteristic, wireless communication support, and low-cost infrastructure. In many applications of WSNs, event detection is the main purpose of users. Moreover, it is crucial to determine where and when that event occurs; thus, the positions of nodes must be identified. Subsequently, in the literature, several location approaches have been proposed to provide nodes with their location. Equipping each node with a Global Positioning System (GPS)-type device is the simplest approach. However, given the large number of nodes, this approach is impractical for many reasons, including the cost of GPS, the limited energy of each node, and the small size of the node[1]. Another

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solution is providing certain nodes, namely, anchors, whose location serves as reference nodes, assisting other nodes in determining their own positions. These reference nodes can be either static anchor positions or moving anchor positions. In Figs. 1 and 2, a static anchor solution is with good location accuracy, many anchors must be used; the mobile anchor technique has shown better performance with regard to cost, network coverage, and accuracy[7, 8]. The idea is to replace the large number of anchors with a single mobile anchor that traverses the network to assist unknown nodes and find their current location. Based on a well-selected path, the anchor can move in the area of interest of the sensor nodes and then stop at certain locations to collect data from the sensor nodes and assist the unknown nodes to be located[9, 10]. Based on the path planning of the mobile anchor, the unknown nodes can estimate their position. Moreover, the mobility of the anchor poses many problems, such as the definition of an online localization algorithm, finding the path with a minimum distance, the effect of the path on the location accuracy, and energy efficiency. This solution presents a new challenge in the localization of WSNs because of its good accuracy. Thus, only one anchor node is used, which can move along a planned or a random trajectory within the network and periodically broadcast its location information to help unknown nodes estimate their positions (see Fig. 1)[8, 9, 11–13]. Furthermore, the different trajectories adopted by the mobile anchor node have different effects on localization accuracy[14]. Many techniques can be used for mobile anchor localization in WSNs. These techniques can be classified into two categories: range-based and range-free localization. Range-based localization algorithms provide the coordinates of unknown nodes, using the distance or angle to establish geometric constraint equations[15]. Examples of such range-based localization algorithms include Received Signal Strength Indicator (RSSI)[16], time of arrival[17], time tifference of arrival[18], and angle of arrival[19]. Range-free localization is based on the connectivity of the network to estimate the position of unknown nodes. Reference [14] presents a review of popular mobile anchor-based localization algorithms in the literature.

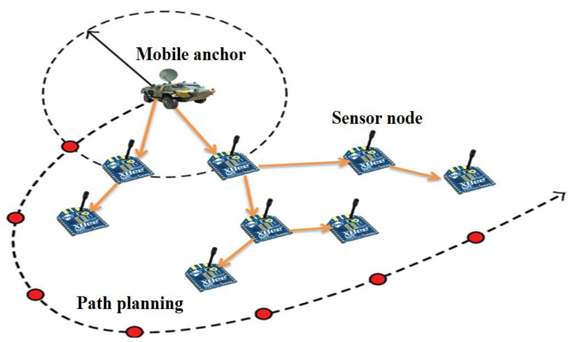


Fig. 1 Localization assisted by mobile anchor node.

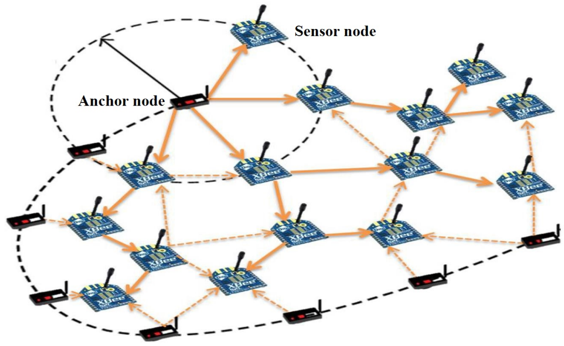


Fig. 2 Localization assisted by static anchor nodes.

In general, localization algorithms based on mobile anchors involve three steps:

(1) Mobile anchor nodes cross the sensing field and periodically transmit beacon packets to other sensor nodes, including their current geographical coordinates.

(2) After receiving the beacon packets, the unknown node updates its hop size and estimates its distances to anchors using the physical properties of communication signals or a heuristic rule.

(3) The unknown node determines its position using an appropriate localization algorithm for online localization.

The main contributions of this paper can be summarized as follows:

- We used the probabilistic heuristic to compute the expected distance between the mobile anchor and unknown nodes.
- We regularized the estimated distance via the regularization factor.
- We introduced the mobile Distance Vector-Hop (DV-Hop) algorithm concept to enhance the localization accuracy via the mobile anchor.

2 Related Work

The DV-Hop algorithm is a well-known range-free localization algorithm. This algorithm presents a landmark for many researchers. In addition, many related algorithms based on DV-Hop have been proposed in the literature. The DV-Hop algorithm has also been improved[20–22]. Methods have been proposed to make the localization more accurate by using a new computing model to estimate the distance between the unknown node and each anchor node in the network. Similarly, an improved DV-Hop has been presented in Ref. [23], the authors introduced a novel computation technique for the distance between the anchor node and unknown nodes by adding the calculated error to the initially estimated distance. A similar approach has been proposed in Ref. [24]. In this technique, the maximum and minimum values of hop counts are introduced to determine the location error, and the error is used in the proposed correction method. Recently, for range-based WSN applications, Yang et al.[25] presented an in-depth analysis by modeling and optimizing the distance estimation error between two nodes using the RSSI signal for a distance-based localization problem. Several error-optimization schemes were compared, including ordinary least squares, generalized feasible least squares, and generalized least squares. Then, the optimization models were tested by simulation, and their influence on the Localization Error (LE) was analyzed. In addition, the presented study considers the relationship between the number of anchors and the LE. In Refs. [26] and [27], Liouane et al. proposed a novel approach for localization in WSNs based on machine learning techniques (named ELM), such as the cascade-ELM and Online Sequence (OS)-ELM, for isotropic and anisotropic WSNs. The proposed localization algorithm exploits two-hidden-layer ELM as machine learning. The first hidden layer estimates the distance between the anchor node and unknown nodes, and the second layer of the ELM estimates the unknown nodes location. In static WSNs, this approach greatly reduces the average LE in comparison with the original DV-Hop heuristic. As sensor nodes are energy constrained, another improvement of the DV-Hop algorithm is proposed in Ref. [28]. In the cited reference, the authors hypothesized that nodes can move around the network. They deploy a single-anchor node as a reference node to localize the moving target node in the network. Once a moving target node comes within the communication range of the anchor node, six virtual anchor nodes with the same range are projected in a circle around the anchor node, and two surrounding virtual anchor nodes are selected to find the two-dimensional (2D) position of the target node.

Peng et al.[29] proposed an optimization of the DV-Hop algorithm based on mobile anchor node. In the latter, mobile anchor was deployed to double radius broadcast their nodes location information to minimize the number of hops between anchor positions and unknown nodes. They used the least squares method to correct the average hop distance of anchor nodes, thus the localization of the nodes becomes more accurate.

Kaur et al.[30] proposed a new localization method using a single mobile anchor and mesh-based path planning models. This technique is primarily developed to improve the original range-free DV-Hop algorithm by using a single mobile anchor and mesh-based path planning models. In a uniform manner, the single mobile anchor moves within the network and identifies its different reference points to determine the location of unknown nodes. Moreover, the proposed localization algorithm via mobile anchors uses linear path planning and triangular path planning. This algorithm improves the traditional range-free DV-Hop heuristic and adapts this heuristic for mobile anchor localization. The entire WSN is divided into small squares; thus, each target node falls under this range at least once, and the mobile anchor provides a linear trajectory or triangular trajectory. The least-squares method is used to estimate the distance from the center of each square cell. The simulation results of the proposed algorithm, which were compared with the original DV-Hop algorithm and improved DV-Hop algorithm by differential evolution algorithm metaheuristic, provide good accuracy and coverage.

Similarly, an improved DV-Hop localization with a Minimum Connected Dominating Set (MCDS) for mobile nodes in WSNs is proposed in Ref. [31]. This algorithm uses the MCDS with anchor nodes; thus, all the unknown nodes can be covered for position estimation. This research paper aims to estimate the positions of unknown nodes by using anchor nodes and network resources efficiently. In the same context, Hu et al.[32] proposed a localization algorithm, namely, mobile anchor centroid localization, which uses a single mobile anchor node. This method is based on radio frequency connectivity during localization; thus, extra hardware cost is not necessary. However, as the single mobile anchor node cannot support the whole mobile environment, it will be resource constrained in the case of an increasing number of unknown nodes. Considerable research has been developed to check the utility of localization using mobile anchor nodes. The research work in Ref. [10] presented a localization method based on a mobile anchor node using trilateration. The proposed algorithm uses mobile anchor nodes that shift along the trilateration trajectory. Han et al.[7] proposed a mobile anchor-based localization algorithm, namely, mobile anchor-assisted localization based on regular hexagons. This technique is based on regular hexagons in 2D WSNs. This algorithm presents good localization accuracy compared with other algorithms in the literature, but it is not effective in the case of randomly deployed nodes. In static WSN mode, improvements in DV-Hop work efficiently to improve the localization accuracy of unknown nodes. Therefore, in this paper, we propose an improved localization algorithm, namely the online DV-Hop algorithm, to address location estimation by using a mobile anchor node and static unknown nodes.

3 DV-Hop Localization Algorithm

The DV-Hop algorithm is a well-known algorithm among range-free localization algorithms. It was developed by Niculescu and Nath[33] and summarized in three different steps.

Step 1: Anchors share their locations and their hop count values, which are initialized to 1 via a beacon packet within the sensing network. Then, by receiving packets from anchors, each unknown node maintains a table that is composed of received information of each anchor (a_i, b_i, h_i), where (a_i, b_i) is the position of anchor i, and h_i is the minimum hop count from anchor i to the unknown node.

Step 2: Each anchor calculates its $HopSize$ (i.e., the average distance of hop) from other anchors using the following equation:

$$HopSize_i = \frac{\sum\limits_{i \neq j}^{n} \sqrt{(a_i - a_j)^2 + (b_i - b_j)^2}}{\sum\limits_{i \neq j}^{n} h_{ij}} \tag{1}$$

where $(a_i\ ,\ b_i)$ and $(a_j,\ b_j)$ are the coordinates of the anchors i and j, respectively, h_{ij} is the minimum hop count between anchors i and j, and n represents the number of anchors. After estimating the average distance of hop, each anchor transmits its $HopSize$ information to nearby nodes in the network. Then, using an appropriate distance estimator, every node can calculate an estimation of its distance to more than three anchors in the network to estimate its position. When the unknown node receives the $HopSize$ information from its nearest anchor, it uses these data to calculate the distance between itself and the neighbor anchor in accordance with the following equation:

$$d_{n_k}^{est} = HopSize_k \times h_{n_k} \tag{2}$$

where $HopSize_k$ is the average distance of one hop that the unknown node n receives from its connected anchor k, and h_{n_k} is the minimum hop count between the unknown node n and anchor node k.

Step 3: Each unknown node calculates its location by multilateration[34]. Let d_n be the estimated distance between an unknown node and anchor node n. (x, y) is the coordinate of the unknown node, and $(a_1, b_1), (a_2, b_2), \ldots, (a_n, b_n)$ are the coordinates of the mobile anchor nodes. We obtain the following set of equations:

$$\begin{cases} (x - a_1)^2 + (y - b_1)^2 = d_1^2, \\ (x - a_2)^2 + (y - b_2)^2 = d_2^2, \\ \qquad \vdots \\ (x - a_n)^2 + (y - b_n)^2 = d_n^2 \end{cases} \tag{3}$$

Then, Eq. (3) can be transformed as follows:

$$AX = B \tag{4}$$

where X, A, and B are calculated in the following:

$$X = \begin{pmatrix} x \\ y \end{pmatrix},$$

$$A = 2 \times \begin{pmatrix} a_1 - a_n & b_1 - b_n \\ a_2 - a_n & b_2 - b_n \\ \vdots & \vdots \\ a_{n-1} - a_n & b_{n-1} - b_n \end{pmatrix},$$

$$B = \begin{pmatrix} a_1^2 + b_1^2 - a_n^2 - b_n^2 + d_n^2 - d_1^2 \\ a_2^2 + b_2^2 - a_n^2 - b_n^2 + d_n^2 - d_2^2 \\ \vdots \\ a_{n-1}^2 + b_{n-1}^2 - a_n^2 - b_n^2 + d_n^2 - d_{(n-1)}^2 \end{pmatrix}.$$

Using the least squares method, we solve Eq. (4) and obtain an estimation of the unknown node coordinates by using the following solution:

$$X = (A^{\mathrm{T}} A)^{-1} A^{\mathrm{T}} B \tag{5}$$

Various improvements of the original DV-Hop algorithm have been reported in previous literature. Most of these techniques are based on the minimum hop count and $HopSize$ optimization, which affects the accuracy of the estimated distance between node and anchor. In this work, we aim to process the localization of unknown nodes using a mobile anchor and the original DV-Hop algorithm. The proposed approach focuses on the displacement of a mobile anchor. Thus, we propose a new formulation of Step 3 of the DV-Hop algorithm.

4 Online DV-Hop Localization Algorithm

In general, sensor nodes (static or mobile) are limited with regard to the most critical resources, such as computing power and memory storage capacity. Sensor nodes are usually unrepeatable, and they become unusable after energy depletion. Indeed, the available small-size memory is in the range of kilobytes, and the limited computational capabilities impose the exploitation of custom localization systems, reduced computing complexity, and reduced memory size. The benefit of the Recursive Least Squares (RLS) algorithm is the online implementation, and matrices need not be inverted, thereby saving computational cost and memory size. Our proposed localization algorithm involves the classical LS DV-Hop algorithm to the RLS localization with a mobile anchor node. Thus, a new formulation of the DV-Hop algorithm is needed.

4.1 HopSize estimation

The DV-Hop algorithm assumes the existence of several anchor nodes for the estimation of inter-node distances and calculates the average hop size among the anchor nodes, indicating that the average hop size will remain the same for all nodes in the network. However, this assumption is not always satisfied in reality, and it cannot be effectively exploited within the framework of a single mobile anchor. Moreover, in addressing the limitation of the original heuristic DV-Hop, we sought to develop a new formulation to accurately estimate the distance among sensor nodes with more precision. This technique replaces the exploitation of the mean distance per hop ($HopSize$) estimated in the second step of the original DV-Hop, which might introduce a large LE for WSN localization. In our proposed method, we use a probabilistic approach for $HopSize$ estimation, and an unknown node will initially estimate the distance to other nodes via an analytic formulation. Indeed, based on the probabilistic estimation, we use an analytical model to estimate inter-node distances while exploiting the number of hops between the mobile anchor position and a normal node position[35, 36]. Then, we assume that each node of the WSN is equipped with an RF module with a communication range R, and all the nodes of the network are randomly deployed in the area of interest based on a uniform distribution forming a connected WSN. Normally, the one-hop between two connected neighboring nodes is between an upper bound equal to R and a lower bound equal to zero. All nodes are deployed in a uniform distribution, and z is the distance between a source node (anchor node) and the destination node (normal node)[35]. The probability distribution function (pdf) can be expressed as

$$f(z)=\frac{2\pi z}{\pi R^2}.$$

Thus, the expected distance to a single hop (Fig. 3a) is calculated in the following:

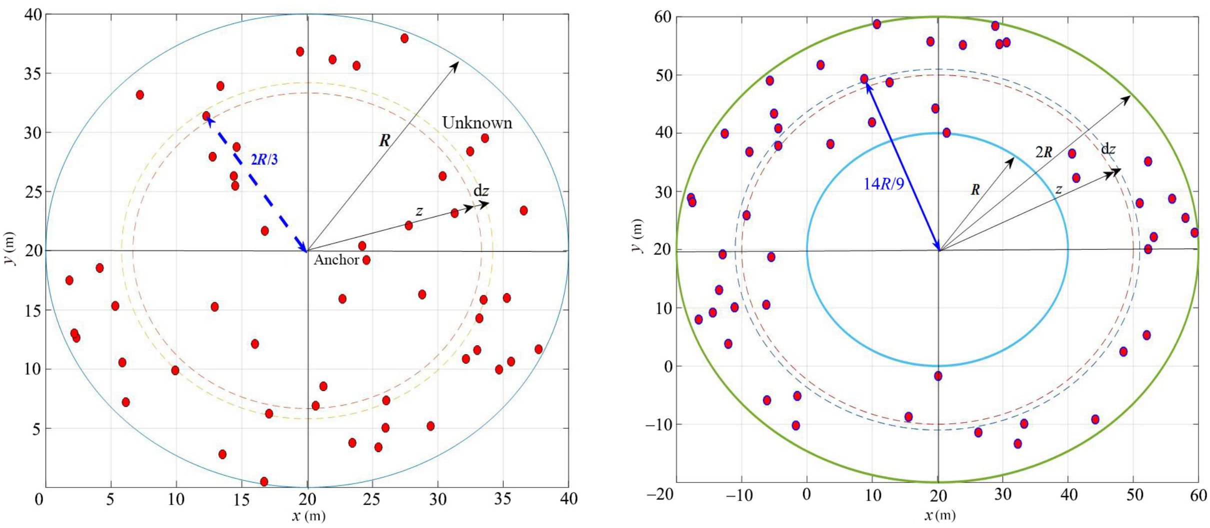
$$E(z)=\int_0^R z f(z)\,\mathrm{d}z=\frac{2}{3}R \tag{6}$$

In addition, the expected distance for 2-hop (Fig. 3b) is calculated in the following:

$$E(z)=\frac{1}{3R^2}\int_R^{2R} z f(z)\,\mathrm{d}z=\frac{14}{9}R \tag{7}$$

In the multi-hop case, see Fig. 4, the expected distance between the source node and destination node located between $(h-1)R$ and hR can be computed via the probability distribution function,

$$f(z)=\frac{2z}{h^2R^2-(h-1)^2R^2} \tag{8}$$



(a) Node distribution for a one-hop case (b) Node distribution for a two-hop case

Fig. 3 Distance estimation for normal distribution in one-hop and two-hop cases.

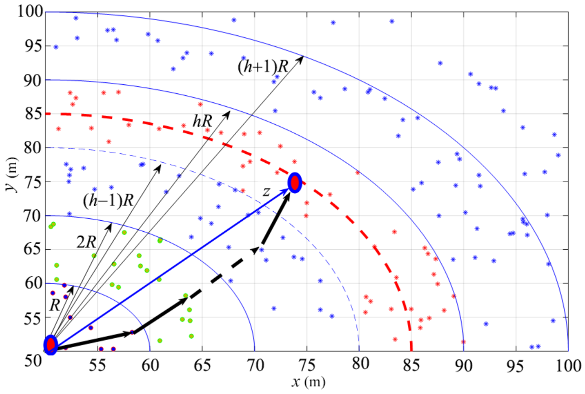


Fig. 4 Correlation between hop counts and distance in multi-hop cases.

Then, the expected distance between two uniformly distributed connected nodes in WSNs can be approximated,

$$E(z) = \int_{(h-1)R}^{hR} z f(z)\,\mathrm{d}z = \frac{2}{3}\frac{h^3-(h-1)^3}{h^2-(h-1)^2}R \quad (9)$$

Thus, if we introduce a regularization factor with imprecision estimation, where $\alpha \in [0, 95, \ldots, 1]$, then the expected distance at h-hops can be computed in the following:

$$E(z) = \frac{2}{3}\frac{\alpha h^3-(h-1)^3}{h^2-(h-1)^2}R \quad (10)$$

4.2 Mobile DV-Hop localization algorithm

In Step 3 of the original DV-Hop algorithm which uses the trilateration model given in Fig. 5, when we consider a mobile anchor that assists localization, at the instant (t), we study the distance $Mn(t)$ between n unknown nodes and the mobile anchor node, which is defined as follows.

Let $(a(t), b(t))$ be the position P of the mobile anchor at instant t. At the instant t,

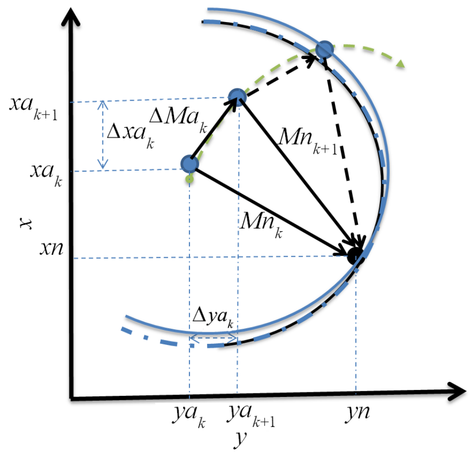


Fig. 5 Localization computation by using a mobile anchor node.

$$(x-a(t))^2 + (y-b(t))^2 = Mn(t)^2 \quad (11)$$

Then,

$$-2xa(t) - 2yb(t) + x^2 + y^2 + Ma(t)^2 = Mn(t)^2 \quad (12)$$

where $Ma(t)^2 = a(t)^2 + b(t)^2$.

The derivative function of Eq. (12) with x and y as constants is measured as follows:

$$x\frac{\mathrm{d}a(t)}{\mathrm{d}t} + y\frac{\mathrm{d}b(t)}{\mathrm{d}t} = Ma(t)\frac{\mathrm{d}Ma(t)}{\mathrm{d}t} - Mn(t)\frac{\mathrm{d}Mn(t)}{\mathrm{d}t} \quad (13)$$

where $(x\ ,\ y)$ is the coordinate of the unknown node, and $(a(t), b(t))$ are the positions of mobile anchor at the instant $t = kT$, where T is the sampling time.

If we approximate $\dfrac{\mathrm{d}z(t)}{\mathrm{d}t}$ using the Euler derivative approximation $\dfrac{zk - zk - 1}{T} = \dfrac{\Delta z}{T}$, then Eq. (13) is presented as follows:

$$x\Delta a + y\Delta b = \big(Ma\Delta(Ma) - Mn\Delta(Mn)\big) \quad (14)$$

At the anchor position P_k, Eq. (14) can be transformed as follows:

$$P_k X = B_k \quad (15)$$

where X, P_k, and B_k are calculated as follows:

$$X = \begin{pmatrix} x \\ y \end{pmatrix},$$

$$P_k = \begin{pmatrix} \Delta a & \Delta b \end{pmatrix},$$

$$B_k = \big(Ma\Delta(Ma) - Mn\Delta(Mn)\big).$$

Then, at the anchor position P_k and using the least squares method, we solve Eq. (15) and obtain an estimation of the unknown node coordinates by using the following solution:

$$X = (P_k^{\mathrm{T}} P_k)^{-1} P_k^{\mathrm{T}} B_k \quad (16)$$

4.3 Online DV-Hop localization algorithm

In parametric identification of the linear system and extreme machine learning process, the RLS algorithm recursively solves the least squares problem. At each iteration, when a new anchor position is available, localization is updated recursively, minimizing the computational effort and the exploited memory size of the sensor node. Next, we propose an online DV-Hop algorithm to recursively approximate the position of the unknown node when the anchor moves to a new position at $(k+1)T$,

$$X = (P_{k+1}^{\mathrm{T}} P_{k+1})^{-1} P_{k+1}^{\mathrm{T}} B_{k+1} \quad (17)$$

At the anchor position p_{k+1}, the following equation must be determined:

$$\begin{bmatrix} P_k \\ p_{k+1} \end{bmatrix} X = \begin{bmatrix} B_k \\ b_{k+1} \end{bmatrix} \tag{18}$$

If we note

$$\Psi_{k+1} = \begin{bmatrix} P_k \\ p_{k+1} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} P_k \\ p_{k+1} \end{bmatrix} \tag{19}$$

Then, the following equation is obtained:

$$X_{k+1} = \Psi_{k+1}^{-1} \begin{bmatrix} P_k \\ p_{k+1} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} B_k \\ b_{k+1} \end{bmatrix} \tag{20}$$

Reorganizing Eq. (20), the unknown node position can be estimated as follows:

$$X_{k+1} = X_k + \Psi_{k+1} p_{k+1}(b_{k+1} - p_{k+1}^{\mathrm{T}} X_k) \tag{21}$$

where X_k represents the estimated coordinates of the unknown nodes at the anchor position k. The updated recursive formula for Ψ_{k+1} is calculated as follows:

$$\Psi_{k+1} = \Psi_k - \frac{\Psi_k p_{k+1} p_{k+1}^{\mathrm{T}} \Psi_k}{I_d + p_{k+1}^{\mathrm{T}} \Psi_k p_{k+1}} \tag{22}$$

where I_d is the identity matrix.

• No matrix inversions are required.

• The computation complexity of the algorithm is $O_{(n^2)}$.

• The covariance matrix Ψ is estimated via a simple update. Initially, high Ψ_0 is to be expected, and we must assign a high value to $\beta \times I_d$.

• If we have some prior information about the unknown nodes X_k, then this information will be used to initialize the algorithm, and the typical initialization is $X_0 = 0$.

Algorithm 1 exhibits the pseudo-code of our proposed mobile DV-Hop algorithm for localization in WSNs.

4.4 Path planning of the mobile anchor

The success of the mobile anchor node-assisted localization depends on the selected path planning. The best option of the mobile anchor trajectory provides good accuracy and acceptable energy consumption. Based on the option of trajectory and localization, the mobile anchor node moves around the network and broadcasts beacon packets and their location information to localize the set of unknown nodes. Recently, many research papers focused on the static path planning optimization of the mobile anchor in 2D WSNs, including Scan, Double-Scan, Hilbert[37], Circular, S-curve[38, 39], Lmat[10], and Random Way Point (RWP). In the majority of the localization schemes, the localization process selects three noncolinear positions of the mobile anchor node and applies the appropriate algorithm to estimate the position of the unknown nodes[37]. Figure 6 shows six variants of path planning. The six-path planning is evaluated in the simulation of our mobile anchor localization.

Algorithm 1 Mobile DV-Hop algorithm

Input:
- Sensor nodes randomly deployed in the sensing field
- Communication range R to be specified
- Path planning specification for mobile anchor nodes
- Unknown nodes $[1, 2, \ldots, n]$ to be localized

Output: Position estimation of the unknown node X^{est}

Begin

(1) **Initialization**

(a) Introduce α; // The regularization factor for distance hop estimation.

(b) $X_0 = 0$; // Initialization of the unknown nodes positions.

(c) $\Psi_0 = \beta \times I_d$; // Initial covariance matrix Ψ, where β is a very large positive number and I_d is the identity matrix.

(2) Picking the initial position of anchor node P_0.

(3) **For** (each anchor position p_k) **Do**

(a) Compute the minimum hop count h_{n_k} between anchor position p_k and unknown node n;

(b) Compute the estimated distance-hop d_{n_k},
$d_{n_k} = \frac{2}{3} \frac{\alpha h_{n_k}^3 - (h_{n_k}-1)^3}{h_{n_k}^2 - (h_{n_k}-1)^2} R$;

(c) Position estimation X_{k+1} of an unknown node using the RLS method,
$\Psi_{k+1} = \Psi_k - \frac{\Psi_k p_{k+1} p_{k+1}^{\mathrm{T}} \Psi_k}{Id + p_{k+1}^{\mathrm{T}} \Psi_k p_{k+1}}$,
$X_{k+1} = X_k + \Psi_{k+1} p_{k+1}(b_{k+1} - p_{k+1}^{\mathrm{T}} X_k)$.

End for

(4) **Return** X^{est} // Estimated coordinates of unknown nodes

End

5 Performance Evaluation

Simulations are performed with Matlab tools to evaluate the performance of the proposed online DV-Hop localization algorithm in the case of isotropic networks and rang-free scenarios. By trial and error, the regularization factor given in Eq. (10) is fixed for all simulation cases at α = 0.945. The Cumulative Distribution Function (CDF) of the LE is the metric used to evaluate the performance of the proposed localization algorithm. The normalized LE characterizes the localization accuracy and the average LE, and the latter is defined as follows:

$$\mathrm{LE} = \sum_{i=1}^{N} \frac{\sqrt{(x_i^{est} - x_i)^2 + (y_i^{est} - y_i)^2}}{N_u} \tag{23}$$

where N_u is the number of unknown nodes. The (x_i, y_i) are real coordinates and the (x_i^{est}, y_i^{est}) are estimated coordinates of the i-th unknown sensor node position.

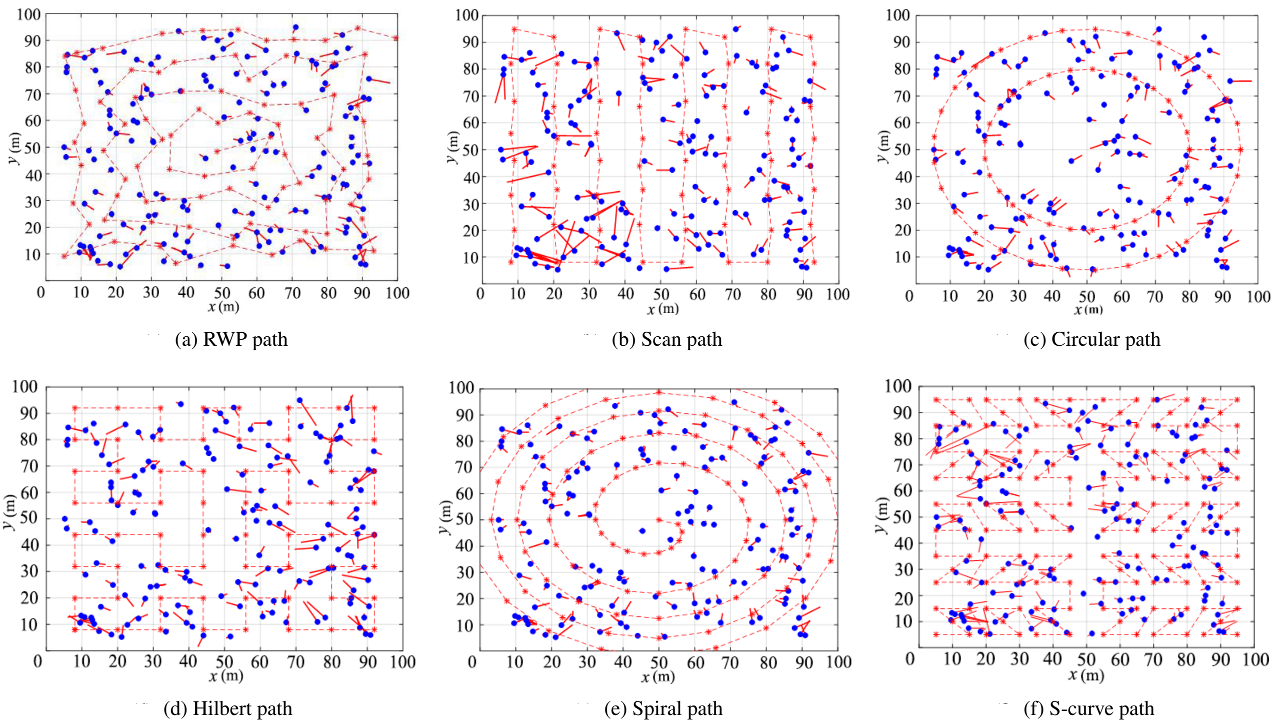


Fig. 6 Localization results with different mobile anchor trajectories.

For successful connectivity among all nodes in WSNs, the communication range must be consistent with the following constraint:

$$R \geqslant 2 \times \sqrt{\frac{A}{N}} \tag{24}$$

where A represents the area of the node deployment zone and N is the total number of nodes to be located.

5.1 Simulation results

The simulations are performed with the random deployment distribution of nodes with different anchor path planning, including RWP, Scan, Circular, Hilbert, Spiral, and S-curve. In ensuring the connectivity among nodes, the communication range R of all nodes is assumed to be equal to $R = 20$ m. In the simulation case, Fig. 6 provides the example of localization results of unknown sensor nodes by the online DV-Hop algorithm for different anchor path planning scenarios. In Fig. 6, blue point denotes the real location of the unknown nodes; the blue straight line represents the LEs between exact and estimated positions, and the red star points denote the mobile position.

Figure 7 provides the LE and CDF achieved by the online DV-Hop algorithm for RWP, Scan, Hilbert, Spiral, S-curve, and the Circular anchor path planning. In this case, Spiral, RWP, Hilbert, and Circular achieve better localization accuracy when compared with the Scan

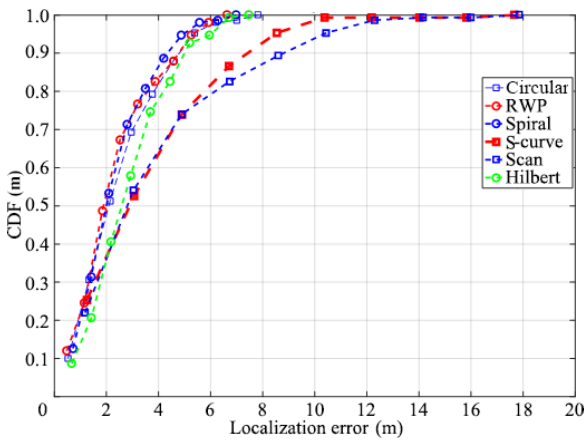


Fig. 7 CDF results for RWP, Scan, Circular, Hilbert, Spiral, and S-curve path trajectories.

and S-curve paths. Table 1 summarizes the accuracy localization results of the proposed online DV-Hop localization algorithm. For example, in the case of Spiral, RWP, Hilbert, and Circular path scenarios, 85% of the unknown sensor node positions could be estimated with LE less than or equal to $0.2R$ (R is the communication range). By contrast, Scan and S-curve path scenarios can obtain 65% of unknown positions with the same LE ($0.2R$). However, 95% of unknown positions could be estimated with LE less than or equal to $0.5R$. However, except for the Z-curve and Scan path, 100% of unknown positions could be estimated with an accuracy less than

Table 1 Accuracy localization results of the online DV-Hop localization.

(%)

Algorithm	LE				
	$\leqslant 0.1R$	$\leqslant 0.2R$	$\leqslant 0.3R$	$\leqslant 0.4R$	$\leqslant 0.5R$
Spiral	55	88	98	100	100
RWP	55	82	95	100	100
Circular	55	80	93	100	100
Hilbert	50	78	90	100	100
S-curve	30	65	80	92	98
Scan	30	65	81	88	95

or equal to $0.5R$. As shown in Table 1, LE resulting from the proposed online DV-Hop algorithm is well adapted for the mobile anchor localization concept, and it can provide acceptable average localization for all proposed anchor path planning scenarios.

Table 2 shows the statistical results of LE in different path-planning anchor positions. The results are for 50 simulation runs. Scan and Hilbert path planning have co-linearity issues because of the movement of the beacon node in a straight line. The spiral and RWP paths provide the lowest location error compared with other suggested paths with regard to the mean, maximum, minimum, and standard deviation of LE because the anchor path successfully overcomes co-linearity.

5.2 Comparison results

In this section, we aim to evaluate the performance results of the online DV-Hop algorithm versus other mobile anchor localization algorithms, namely the triangular path model and linear path model. We perform simulations to compare performances under the same scenarios by comparing the metric of the LE. The performances of our algorithm are compared with the best results given in Ref. [30] which concerns the triangular path model and linear path model algorithms. In the first experiment, we consider the spiral path planning trajectory, and the effect of the variation of sensor node amount on the LEs is evaluated. The

Table 2 Statistical results of the online DV-Hop localization errors.

(m)

Algorithm	Path			
	Min	Max	Mean	Standard deviation
Spiral	0.118	6.217	2.483	1.656
RWP	0.135	6.955	2.564	1.155
Circular	0.365	9.311	2.585	1.421
Hilbert	0.332	8.576	4.272	2.770
S-curve	0.254	14.777	4.610	3.309
Scan	1.898	17.844	5.127	1.604

communication range of all nodes is adjusted to 20 m. The total number of sensor nodes varies from 100 to 300. Figure 8 shows the variation of the LE with the variation of the total number of nodes. For the online DV-Hop algorithm, as shown in Fig. 8, the LE decreases when the total amount of nodes increases. These results can increase the number of nodes to increase network connectivity. When the number of neighboring nodes increases for each node the minimum hop count decreases.

Under these scenarios, the proposed algorithm has the smallest LE. For example, in the case of low-density WSNs (100 sensor nodes), LE given by the online DV-Hop algorithm is improved by 2% versus the triangular path model algorithm given in Ref. [30]. However, in the case of high-density WSNs (300 sensor nodes), LE of the proposed algorithm is 13% versus 28% for the triangular path model algorithm, and LE is reduced by over 50%. Therefore, the proposed online DV-Hop algorithm performs well in the case of high-density WSNs.

In this second experiment, the effect of the variation of the communication range of nodes on LE is evaluated. We consider that the WSN is composed of 300 nodes, and the communication range of all nodes varies from 10 m–40 m. Figure 9 provides a comparison of LE given by the online DV-Hop algorithm versus the triangular path model algorithm for different communication ranges R. Based on Fig. 9, for $R = 10$ m, the online DV-Hop algorithm performs poorly compared with the triangular path model because

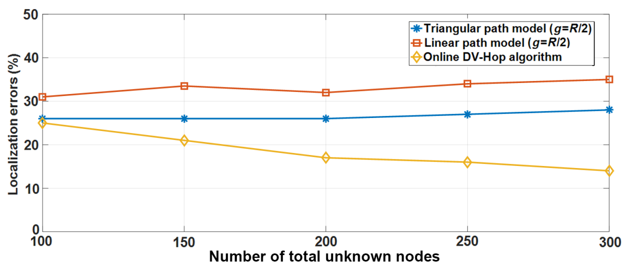


Fig. 8 Localization errors versus total unknown nodes.

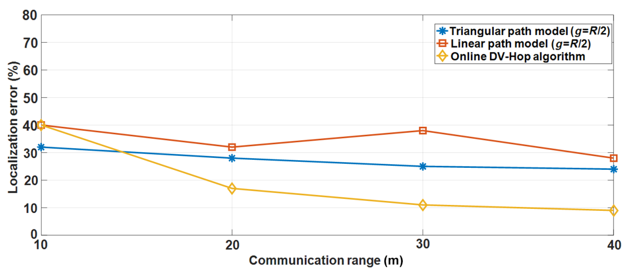


Fig. 9 Localization errors versus communication range.

$R = 10\,\text{m}$ does not respect the connectivity constraint given by Formula (24). Based on this constraint, the communication radius should be greater than $11.54\,\text{m}$. On the contrary, for $R = 20\,\text{m}$, $30\,\text{m}$, and $40\,\text{m}$, the proposed algorithm performs better than the triangular path model algorithm. As shown in Figs. 8 and 9, under all scenarios with regard to the constraint shown in Formula (24), the proposed algorithm provides high localization accuracy by up to 50% when compared with other localization algorithms given in Ref. [30].

6 Conclusion

In this paper, a mobile anchor localization algorithm has been proposed to optimize node localization accuracy in WSNs. The suggested online DV-Hop algorithm is based on the probabilistic approach to estimate the WSN HopSize and RLS algorithm for localization. The concepts of the algorithm represent a new way to tackle WSN localization via mobile anchor, which is a primordial task for collecting, analyzing, and tracking the sensed zone information. The online DV-Hop algorithm has been tested for different path scenarios in range-free cases and isotropic environments. For performance evaluation, the CDF of LE has been applied. The experiment results show that the regularization factor for $HopSize$ estimation and the path planning of the mobile anchor play a preponderant role in ameliorating localization accuracy. These advantages of the mobile anchor make the online DV-Hop algorithm a potential candidate for treating the WSN localization problem in real-time processing. The real-time processing and FPGA implementation of the proposed algorithms will be treated in future work.

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