



Enhanced Distance Vector Hop Localization Algorithm based on Hop Threshold and Weighted Matrix for Wireless Sensor Networks

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Abstract: The Distance Vector Hop (DV-Hop) algorithm is a frequently used localization method, which is widely applied in location-based applications for its implement-efficient. However, it has poor localization accuracy, especially in complex unevenly distributed network environment. This study proposed an enhanced range-free localization scheme based on hop threshold and weighted matrix to address this issue, named as TWDV-Hop. First, we build considerable experiments to analyze the distributed law between hop count and average hop size error. Large hop count will be cut out to optimize average hop size based on analysis results, since it is the main reason that led to large location error for its inaccuracy. Then, weighted matrix is introduced to instead of basic least squares in the third phase to narrow location error brought by non-linear equation. Finally, extensive experiments were conducted for several evaluation metrics, as localization accuracy, energy consumption cost under effected parameters in terms of anchor node density, communication range etc. Simulation results demonstrated the TWDV-Hop algorithm had outstanding performance in accuracy and energy consumption. The localization error is decreased more than 60%, when compared with latest new literatures. Especially, the maximum reduction localization error reached up to 75%. Moreover, the average localization error is lower 3.5m, which can meet location-based application requirements at a certain level.

Keywords: Wireless sensor networks (WSNs), DV-Hop localization algorithm, Average hop size, Beacon node

1. INTRODUCTION

The new concept of Internet of Things (IOT) and artificial intelligence technique has fostered under the umbrella of high embedded technique. Wireless sensor networks (WSNs) as the core telecommunication technology and fundamental part of IOT, it has become an emerging cross-spot research field. WSNs can be efficiently integrated with internet based on combined information collection, communication, and computing capabilities into one combination, that realize the information transmission and interconnection between people and things, and between things to form the Internet of Things [1]. Node localization technology as most core supporting technologies of WSNs, which can provide location information for sensor nodes and meanwhile afford technical support for geographic location-based protocol and target tracking [2]. In addition, location information is the prerequisite for sensor network

monitoring and control, since most monitoring or tracking information need to be accompanied with corresponding location information, otherwise, these data will be lost collect meaning [1-2].

One of the easiest ways to obtain location information for unknown nodes is attached global positioning system (GPS). However, it is impossible to equipped it to all sensor nodes, since GPS will largely increase node size, power consumption, and hardware cost, especially, it cannot work in an indoor environment [3]. So, only fewer nodes carried GPS and this type of nodes called as beacon nodes or anchor nodes, the others named as unknown nodes or target nodes. The localization algorithm adopted few beacon nodes obtain the location information of unknown nodes. In recent days, a great large numbers of localization algorithms have been introduced. It is broadly divided into two divisions, range-based localization scheme and range-free localization scheme based on whether inquire to attach additional device to measure distance or angle [5-6]. The



range-based localization algorithm has high location accuracy, but its requirements of hardware and cost is high. In addition, it must maintain strict clock synchronization between nodes. The representative ranging algorithms are Received Signal Strength Indicator (RSSI) [7], Time of Arrival (ToA) [8], Time Difference of Arrival (TDoA) [8] and Angle of Arrival (AoA) [9], etc. In contrast, range-free localization technology has no special hardware requirement and is less affected by environment and easy to implement. It conquered most disadvantage of range-based method and is more suitable for large-scale location-based applications in WSNs, especially for large size and low energy consumption network. Traditional range-free localization scheme includes Amorphous [10], Centroid [11], Approximate Point in Triangle Test (APIT) [12] and Distance Vector-Hop (DV-Hop) [13], etc.

DV-Hop algorithm as one of most popular localization technologies in WSNs. It only utilized beacon nodes broadcast information in network to locate node, which can efficiently save hardware costs and energy consumption. According to the location idea of DV-Hop scheme, it can obtain reasonable average hop size distance and more accuracy position when network nodes are densely and evenly deployed, especially network is isotropic. However, in actual application environment, nodes are often randomly distributed and network topology is easily presented as anisotropy. Hence, localization accuracy of DV-Hop went down dramatically under random sparse network topology.

In recent years, a great large number of suitable improvement strategies for basic DV-Hop localization algorithm have been widely studied. An abounding researcher have proposed enhanced algorithms from different angles. A modified DV-Hop algorithm is proposed in [14], that based on Poisson distribution probability statistical function to select accurate beacon nodes for calculate distance of unknown node. The concept of fractional hop count is introduced to minimize hop error based on RSSI technology in [15]. Then, a weighted coefficient is applied to correct the average hop distance. Finally, Differential Evolution (DE) algorithm is explored to solve non-linear equation problem. Simulation results shown HDCDV-Hop algorithm improve accuracy by 10% with low complexity and better efficient. Most of enhanced algorithm improve localization accuracy to a certain stage. Based on above deficiencies, this article mainly focuses on two aspects, enhance average hop size and optimize method to solve non-linear equation.

The structure of rest paper is as follows. Recently advanced literatures research on DV-Hop localization techniques are illustrated in Section 2. In Section 3, traditional DV-Hop is introduced. Deeply error analysis of the DV-Hop localization scheme is presented in Section 4. In Section 5, our enhanced DV-hop localization algorithm, TWDV-Hop is comprehensively presented. Experimental

outcomes and discussion are elaborated in Section 6. Eventually, comprehensive conclusions and the work will be done in future are formulated in Section 7.

2. RELATED WORKS

In recent years, it has been several literatures on how to enhance DV-Hop localization scheme, which focus on different concern points. A fast, accurate and easy DV-Hop localization algorithm, named IDVLA is introduced in [16]. It computes the average of entire hop distances. In the third phase, a 2-D hyperbolic location method is employed to instead of the least squares method to solve nonlinear equation issue. An upgraded DV-Hop formulated to address big error by enhance one hop count and weight hop size in [17]. One hop count is graded into m levels depended on how many of communicable anchor nodes. RSSI technology is employed to rectify hop value in the light of segmentation hop count. In addition, the average hop size is modified based on each difference error. Subsequently, weighted value is employed to recalculate hop size. A fresh metric is presented to rectify hop size in [18], which is depend on whole network beacon node hop distance error. An innovative algorithm, PMDV-Hop, which on the basis of error-compensation is introduced in paper [19]. To further enhance location accuracy, inequality constraints is utilized to narrow location error by least-square approach. PMDV-Hop shows advanced efficient, remarkable accuracy and fast convergence speed, but with extremely high energy consumption and complex computation. Two new algorithms are proposed in [20], Checkout DV-hop localization algorithm and Selective 3-beacon DV-hop localization algorithm, that based on improved protocol to improve the accuracy. The idea of improved algorithm is only using 3 nearest beacons for unknown node instead of using all communicable beacons to compute its location. However, this scheme has a high requirement that each two sensor nodes must with similar connectivity and similar location. The design is not always satisfied because the deployment of all-sensor node is randomly.

The concept of proportional parameter is introduced to narrow average hop size error in [21]. The localization accuracy increased 10.2% comparing with traditional DV-Hop. In basic DV-Hop localization algorithm, the hop size and nearest hop count is estimated, so it will great effect the localization accuracy. In [22], it employed actual distance between beacon node to correct hop size. Then, correction factor is introduced to reevaluate minimum hop count. An improved method is also proposed in [23] to deal with above issue. Firstly, the author introduced a concept of adaptive threshold to refine hop count. Hereafter, the hop size of each anchor node is re-correct by employ weighted normalization. Finally, the experiments are simulated under random and nonrandom environment, which has an obvious better performance in both scenarios. A Half-measure weighted centroid method is proposed in [24], it

optimizes optical distance and short paths between beacon nodes.

Most previous work only consider only one performance metric like localization accuracy. A new DV-Hop approach combined weighted centroid localization scheme is introduced in paper [25] that not only consider location error but also energy consumption. In this work, hop counts that is larger than two will be discard, theoretical and simulation proved localization accuracy is greatly enhanced, and largely reduced consumption. It compared four typical localization algorithms under same experiment environment in paper [26]. Analysis result shown DV-Hop with high stability under even distributed network.

Intelligent algorithms have outstanding advantage in solving complex optimization problems. An enhanced adaptive cuckoo search algorithm (HMCS) is introduced to reduce location error for DV-Hop in WSN [27]. In HMCS, the nest population is subdivided into three parts based on fitness value to control step size. Furthermore, Lévy Flight is utilized to enhance search ability. In addition, hop counts are corrected by weighted factor that is based on the ideal calculate number. One hop count is evenly divided into three part to minimize estimated distance error gap and area is represented distance for one hop count. A mixed global swarm optimization (GSO) adopted chaotic strategy (MC-GSO) is introduced to instead of least square method, named as MGDV-Hop [28]. The search ability and robustness greatly enhanced by adopt chaos mutation and chaotic inertia weight. It is notable that MGDV-Hop has a superior performance not only under localization accuracy but also under location coverage and energy consumption. Bacterial Foraging Optimization (BFO) is employed to reduce the localization error by recorrect the estimated coordinate of unknown node [29].

An improved PSO is adopted to enhance DV-Hop in paper [30]. It developed a mathematical model to address nonlinear equation issues. It is worth noting that typical PSO is easy to sink into local optima, and has a limited convergence speed of with fixed learning factor. To address this issue, an advantageous PSO is proposed for DV-Hop in [31]. In this work, two quickening factors in learning factor are introduced to accelerate convergence speed and search ability. Moreover, inertia weighted is updated based on threshold value. Simulation consequents show promoted PSO has a superior performance in convergence speed and localization accuracy. However, it increased the complexity of basic DV-Hop algorithm and positioning time.

All above algorithms have boost localization accuracy to certain degree, but most of them at the expense of computational complexity and communication overhead. Therefore, we proposed our enhanced localization approach, TWDV-Hop to heighten localization accuracy. The traditional DV-Hop localization algorithm is introduced in next Section.

3. TRADITIONAL DV-HOP ALGORITHM

DV-Hop localization scheme was first put forward by Dragons Niculescu and his team [13] for 2D WSNs. It incorporates with three basic steps.

Step 1: Calculate Minimum Hop Counts

Each beacon node broadcasts a specific packet, format as $\{id; (x_i, y_i), h_i\}$, here, id is the identity of beacon node, (x_i, y_i) denotes the location of beacon nodes, h_i represents the minimum hop, the initial value is zero. Every communicable neighbor node store received information table, added 1 hop count then forwarded updated information to its neighbor nodes. If received information is from same beacon node and greater than previous hop count, the information will be discarded.

Here, taken Fig. 1 as an instance of DV-Hop localization algorithm, A_1 , A_2 and A_3 represents beacon nodes, and the others are unknown nodes. It is assumed U_i is the one unknow node that need to be tracked down. The shortest hop count of A_1 to A_2 , A_2 to A_3 and A_1 to A_3 is 2, 5 and 7, respectively, based on **Step 1**. The minimum hop of U_i to A_1 , A_2 and A_3 is 4, 2 and 3, respectively.

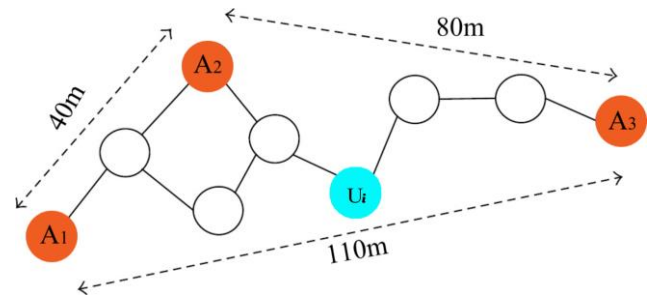


Figure 1. An illustration of DV-Hop localization algorithm

A. Step2: Calculate Average Hop Size (AHS)

Each beacon node can obtain its minimum hop to other beacon nodes after first step finished. The average hop size (AHS) can be obtained by adopted Equation (1) to calculate for each beacon node.

$$AvgHopSize_i = \frac{\sum_{i \neq j}^m \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j}^m H_{ij}} \quad (1)$$

Where (x_i, y_i) , and (x_j, y_j) are the coordinate of beacon node i and j , respectively. H_{ij} is the shortest hop count between i and j . $AvgHopSize_i$ represents the average hop size of i .

Here, we still take Fig. 1 as an illustration. The AHS of A_1 , A_2 and A_3 can be estimated as following.

$$AvgHopSize_{A_1} = (40 + 110) / (2+7) = 16.67$$

$$AvgHopSize_{A_2} = (40 + 80) / (2+5) = 17.14$$

$$AvgHopSize_{A_3} = (110 + 80) / (7+5) = 15.83$$

Equation (2) is employed to calculate estimate distance d_{ij} between beacon node i and unknown node U .

$$d_{iu} = AvgHopSize_i \times H_{iu} \quad (2)$$

Since the minimum hop of U_i to A_1, A_2 and A_3 is 4, 2 and 3, so here, it chose $AvgHopSize_{A_2}$ to estimate the distance of U_i to A_1, A_2 and A_3 , it can be obtained by Equation (2).

$$d_{A_1 U_i} = 17.14 \times 4 = 68.56$$

$$d_{A_2 U_i} = 17.14 \times 2 = 32.48$$

$$d_{A_3 U_i} = 17.14 \times 3 = 51.42$$

After obtained AHS, each beacon node broadcasts it to the entire networks. The unknown node only received AHS from the closest beacon node and pass it to neighbour node.

$$\begin{aligned} 2(x_n - x_1)x_u + 2(y_n - y_1)y_u &= d_1^2 - d_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ 2(x_n - x_2)x_u + 2(y_n - y_2)y_u &= d_2^2 - d_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 \\ &\vdots \end{aligned} \quad (4)$$

$$2(x_{n-1} - x_n)x_u + 2(y_{n-1} - y_n)y_u = d_{n-1}^2 - d_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2$$

Equation (4) can be formulated into $AX=B$, see as follow.

$$A = -2 \times \begin{bmatrix} x_1 - x_n & y_1 - y_n \\ x_2 - x_n & y_2 - y_n \\ \vdots & \vdots \\ x_{n-1} - x_n & y_{n-1} - y_n \end{bmatrix} \quad (5)$$

$$X = \begin{bmatrix} x_u \\ y_u \end{bmatrix} \quad (6)$$

$$B = \begin{bmatrix} d_1^2 - d_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ d_2^2 - d_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 \\ \vdots \\ d_{n-1}^2 - d_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 \end{bmatrix} \quad (7)$$

Equation (8) can be employed to get the coordinate (x_u, y_u) of unknown node, see as following.

$$X = (A^T A)^{-1} A^T B \quad (8)$$

4. PERFORMANCE ANALYSIS OF DV-HOP LOCALIZATION ALGORITHM

A. Error analysis of Average Hop Size

It is utilized multiple hop size to approximate straight-line distance in DV-Hop algorithm. Hence, there is inevitable error of the estimate coordinate in unknown node. This can be verified in Fig.2. The Fig.2 demonstrated that the estimated distance of AHS multiple hop count is the sum of all polylines between A and B,

B. Step3: Estimate Coordinate of Unknown Node

The least squares method is utilized to calculate the coordinate of unknown node, once it obtained three communicable beacon nodes.

Here, (x_u, y_u) represents the coordinates of unknown node U , and d_{iu} is the estimated distance between u and A_i , $i \in \{1, 2, 3 \dots n\}$, d_{iu} can be obtained by Equation (2).

$$\begin{aligned} (x_u - x_1)^2 + (y_u - y_1)^2 &= d_{1u}^2 \\ (x_u - x_2)^2 + (y_u - y_2)^2 &= d_{2u}^2 \\ &\vdots \\ (x_u - x_n)^2 + (y_u - y_n)^2 &= d_{nu}^2 \end{aligned} \quad (3)$$

It can be subtracted the last equation of Equation (3) with each one, that can be expressed as follow.

which is significantly larger than the linear distance between A and B.

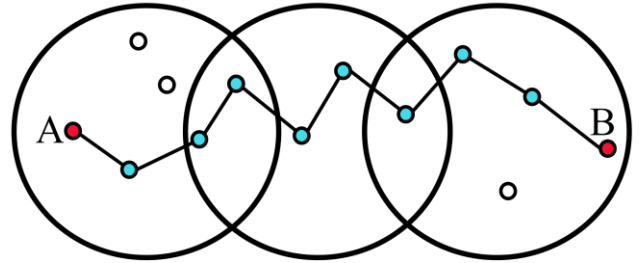


Figure 2. An example of node distribution

Whether estimate AHS is resealable or not that massively determined the localization accuracy. In addition, AHS have a close relationship with hop count, aimed at investigating the relationship between AHS error and hop count, following experiment has conducted in this paper. In this experiment, there are 100 sensor nodes are random distributed in $100m \times 100m$ area, including 30 beacon node and communication range is 25m. The distributed law of hop and AHS error is presented in Fig. 3 and Fig.4.

It can be observed from Fig.3 that the relationship between hop value and hop amount is approximate normal distribution. The maximum hop value is 7 and it with least number amount. Hop value 3 with largest amount, that exceeded 220. The amount of hop value 2 and 4 is round 200. It can be observed form Fig.4 that AHS error demonstrated upward trend with hop value increasing. And the conclusion of more hop counts more AHS error can be conducted in Fig.4. Hop value 2 with minimum error less than 2m, the second and third is hop value 1, 2, respectively. The AHS error of hop value 6 is almost 5 times larger than hop value 2. The sum amount of hop value 4, 5, 6, 7 is one-third of the total number. Therefore, it is urgent to optimize AHS cause large hop value with big error. We proposed large hop value be cut out to optimize AHS based on above analysed results.

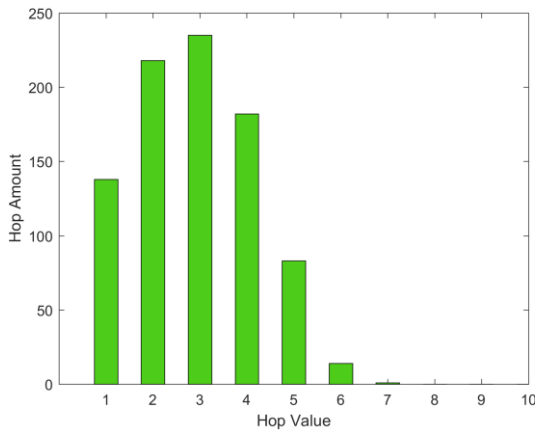


Figure 3. The relationship between hop value and hop amount

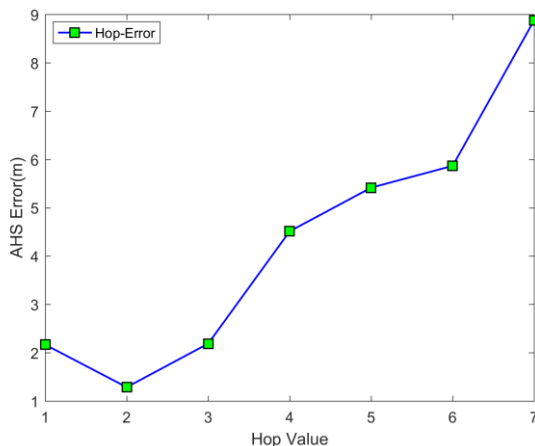


Figure 4. A distribution law between hop value and AHS

B. Error Analysis of Location Technique

2D hyperbolic location method is adopted to solve non-linear equation instead of least squares in [16]. It is reported that improved accuracy to a certain degree than

that using least squares method in traditional DV-Hop algorithm. But it still has large error in the coordinate of unknown node. To better comprehend above issue, basic 2D hyperbolic location method and error analysis term is illustrated in below section.

- 2D hyperbolic Location Technique.

Let (x_u, y_u) be the coordinate of node to be located U . The estimated distance is calculated using the following equations:

$$\begin{aligned} (x_u - x_1)^2 + (y_u - y_1)^2 + \xi_1 &= d_{1u}^2 \\ (x_u - x_2)^2 + (y_u - y_2)^2 + \xi_2 &= d_{2u}^2 \\ &\vdots \\ (x_u - x_n)^2 + (y_u - y_n)^2 + \xi_n &= d_{nu}^2 \end{aligned} \tag{9}$$

Where, ξ_i is the error between estimate and actual distances, and Equation (9) can be expanded as follows:

$$\begin{aligned} -2x_1x_u - 2y_1y_u + x_u^2 + y_u^2 + \xi_1 &= d_{u1}^2 - x_1^2 - y_1^2 \\ -2x_2x_u - 2y_2y_u + x_u^2 + y_u^2 + \xi_2 &= d_{u2}^2 - x_2^2 - y_2^2 \\ &\vdots \\ -2x_nx_u - 2y_ny_u + x_u^2 + y_u^2 + \xi_n &= d_{un}^2 - x_n^2 - y_n^2 \end{aligned} \tag{10}$$

Let $K = x_u^2 + y_u^2$, Equation (10) is expressed in linear form:

$$A \cdot c = B \tag{11}$$

$$\text{Where, } A = \begin{bmatrix} 1 & -2x_1 & -2y_1 \\ 1 & -2x_2 & -2y_2 \\ \vdots & \vdots & \vdots \\ 1 & -2x_n & -2y_n \end{bmatrix}, \quad B =$$

$$\begin{bmatrix} d_{u1}^2 - x_1^2 - y_1^2 \\ d_{u2}^2 - x_2^2 - y_2^2 \\ \vdots \\ d_{un}^2 - x_n^2 - y_n^2 \end{bmatrix}, \quad c = \begin{bmatrix} K \\ x_u \\ y_u \end{bmatrix}$$

In using the least square method to address Equation (11), unknown node U is obtained as follows:

$$c = (A^T A)^{-1} A^T B \tag{12}$$

The unknown node U is

$$[x_u \ y_u]^T = [c(2) \ c(3)]^T \tag{13}$$

- Error Term Analysis

Let unknown node is U , the closest beacon node is I , and the error between estimated and actual distances of unknown node is Δd_{ui} . Assume that the projection of the distance between adjacent nodes is on the shortest path, and obeys the Gaussian distribution of zero mean and variance. Therefore, the mean of Δd_{ui} is zero and the variance is proportional to the minimum hop between U and I .



Based on Equation (10), $\xi_i = 2d_{ui} \times d_{ui} + \Delta d_{ui}^2$. Upon neglecting the second term, the following equation is obtained:

$$\xi_i = 2d_{ui} \times d_{ui} \quad (14)$$

As noted from Equation (14), ξ_i has the characteristics of zero mean and heteroscedasticity. Nevertheless, error ξ_i does not satisfy the same variance, and the classic linear regression model does not hold. The least squares estimation also does not satisfy the optimal linear unbiased estimation. Therefore, the heteroscedasticity of error ξ_i needs to be corrected.

5. PROPOSED ALGORITHM (TWDV-HOP)

Our proposed algorithm, TWDV-Hop is mainly focus on two points to optimize basic DV-Hop localization algorithm. AHS is corrected in **Step 1**, which is the first innovation point, see Section 5.1. The second step is like the traditional approach. The other contribution is in **Step 3**, detail information is illustrated in Section 5.2.

A. AHS Correction

As we discussed in Section 4.1, AHS error increased as hop value enlarge. Accordingly, we proposed large hop value be cut out during in the process of broadcast in **Step 1**. The detail information seen as following.

We adopted information table (ID, X_i , Y_i , Hop_i , $Flag_Hop$) to donate information packet from received nodes. Here, we add one new byte ($Flag_Hop$) in information table. $Flag_Hop$ is utilized to mark whether hop count is larger than 3 or not. If it is true, $Flag_Hop$ is set to be 1, otherwise, it set to be 0. The initial hop count and $Flag_Hop$ are 0.

After network initialization is completed, beacon node will broadcast the information packet contained to the whole network. If the $Flag_Hop$ of received packet is 1, discard this packet. Otherwise, compared hop value with previous one. If received hop count is larger or equal than previous one, discard this packet. Else, keep it and update packet information table. Then, hop count added by 1, judge whether hop count is larger or equal to 3. If it is true, $Flag_Hop$ is set to be 1 and stop forwarding to neighbor nodes. Otherwise, $Flag_Hop$ is still be 0, and continue to transmit to communicable neighbor nodes.

B. Unknown Node Coordinate Correction

New weighted 2D hyperbolic location technique is proposed to reduce location error in **Step 3**. The idea of weighted least squares gives smaller weights with larger variances of error terms. Based on Equation (13), the performance index of the weighted least squares estimation is given in the following:

$$\sigma(c) = [b - Ac]^T W [b - Ac]^T \quad (15)$$

Where, $\sigma(c)$ denotes the sum of squared deviations, while W refers to the positive weighted matrix. In order to determine the partial derivative for c , the following is applied:

$$\frac{\partial}{\partial c} \sigma(c) = \frac{\partial}{\partial c} [b - Ac]^T W [b - Ac]^T = 2A^T W [b - Ac] \quad (16)$$

When Equation (16) is zero, the coordinates of unknown node are determined by considering the extreme value.

$$c_{LSW} = (A^T W A)^{-1} A^T W b \quad (17)$$

Where, c_{LSW} represents weighted least squares estimation, while the estimated error is given below:

$$E\{[c - c_{LSW}][c - c_{LSW}]^T\} = (A^T W A)^{-1} A^T W R_{\xi} W A (A^T W A)^{-1} \quad (18)$$

Where, $R_{\xi} = E\{\xi \xi^T\} = D^T D$, in which D is reversible matrix.

Let $M = A^T D^{-1}$, $N = D W A (A^T W A)^{-1}$. The following equation can be obtained based on Schwarz inequality.

$$N^T N \geq (M N)^T (M M^T)^{-1} (M N) \quad (19)$$

Only one matrix Q can satisfy the equation, which is when $N = M^T Q$. Here, Equation (19) can be expressed as follows:

$$(A^T W A)^{-1} A^T W R_{\xi} W A (A^T W A)^{-1} \geq (A^T R_{\xi} A)^{-1} \quad (20)$$

Equation (20) is satisfied only when $W = R_{\xi}^{-1}$. Based on Equation (13), the error matrix can be expressed as follows:

$$\xi = [\xi_1 \ \xi_2 \ \dots \ \xi_n]^T \quad (21)$$

$$E\{\xi \xi^T\} = \text{diag}(E\{\xi_1 \xi_1\} \ E\{\xi_2 \xi_2\} \ \dots \ E\{\xi_n \xi_n\}) + B \quad (22)$$

$$B = \begin{pmatrix} 0 & E\{\xi_1 \xi_2\} & E\{\xi_1 \xi_n\} \\ E\{\xi_2 \xi_1\} & 0 & E\{\xi_2 \xi_n\} \\ \vdots & \vdots & \vdots \\ E\{\xi_n \xi_1\} & E\{\xi_n \xi_2\} & 0 \end{pmatrix} \quad (23)$$

There are two cases under this condition. If beacon nodes I and J are not on the same line, both Δd_{ui} and Δd_{uj} become independent. Hence, $E\{\xi_i \xi_j\} = 0$. This shows that the distance between adjacent two nodes in the direction of the line is independent. The other case is that when beacon nodes I and J are on the same line, its AHS error and variance are the same. The shortest path between $E\{\xi_i \xi_j\}$ is proportional to the same shortest path between beacon nodes I and J . Considering the distribution characteristics of wireless networks, the probability of collinearity between U , I , and J is extremely small, hence B is negligible and Equation (24) is given as follows:

$$R_{\xi} = \text{diag}(E\{\xi_1\xi_1\} E\{\xi_2\xi_2\} \dots E\{\xi_n\xi_n\}) \quad (24)$$

Based on Equation (14), Equation (25) is obtained, as follows:

$$E\{\xi_i\xi_i\} = 4Hopsiz_e^2 \times h_{ui}^2 \times E\{\Delta d_{ui} \times \Delta d_{ui}\} \quad (25)$$

It is assumed that the variance distance error between adjacent nodes is σ^2 . Therefore,

$$E\{\Delta d_{ui} \times \Delta d_{ui}\} = h_{ui} \times \sigma^2 \quad (26)$$

Equation (24) can be expressed as given below:

$$R_{\xi} = 4Hopsiz_e^2 \times \sigma^2 \times \text{diag}(1/h_{u1}^3, 1/h_{u2}^3, \dots, 1/h_{un}^3) \quad (27)$$

The estimated coordinates can be determined by substituting Equation (27) into Equation (17).

$$\sigma(c) = \sum_{i=1}^n w_i \times (d_{ui}^2 - x_i^2 - y_i^2 - K - 2x_i \times x - 2y_i \times y) = \sum_{i=1}^n w_i \times \xi_i^2 \quad (28)$$

Where w_i refers to the weighted coefficient of the error term, ξ_i :

$$E\{w_i \times \xi_i^2\} = w_i \times 4Hopsiz_e^2 \times h_{ui}^2 \times E\{\Delta d_{ui} \times \Delta d_{ui}\} = 4Hopsiz_e^2 \times \sigma^2 \quad (29)$$

Based on Equation (29), after introducing the weighted matrix, the variance and the corresponding weighted coefficient product of error term, ξ_i , become a constant and independent of i .

The work flow chart of the TWDV-Hop localization algorithm is illustrated in Fig. 5.

6. EXPERIMENTAL RESULTS AND DISCUSSION

A. Evaluation Criteria

There are two evaluation metrics, Localization accuracy and energy consumption overhead are utilized to assess the achievement of TWDV-Hop.

• Accuracy Metrics

(1) Localization Error (LE)

The localization error (LE) is an error between the actual and calculated coordinate of target node, the expression is shown in Equation (30).

$$LE = \sqrt{(x_u - x_a)^2 + (y_u - y_a)^2} \quad (30)$$

(2) Localization Error Radius (LER)

The LER is the ratio of the average LE to communication range R , as given in the following:

$$LER = \frac{\sum_{u,a=1}^n \sqrt{(x_u - x_a)^2 + (y_u - y_a)^2}}{n \times R} \quad (31)$$

• Energy Consumption Metric

Energy consumption is a crucial metric to evaluate the performance of the localization algorithm, which is evaluated by the number of transmitted and received packets during the localization process. The reduction in communication overhead is an important accomplishment of saving energy.

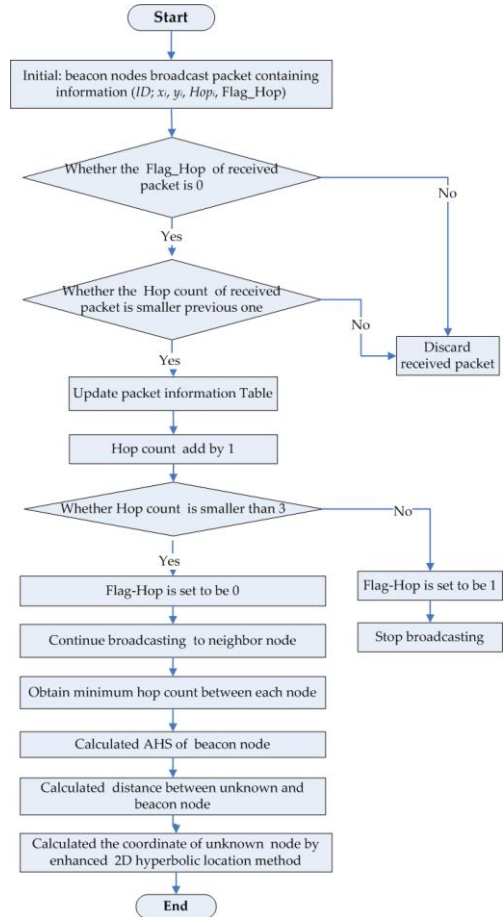


Figure 5. The flow chart of TWDV-Hop

B. Experimental Environment

An instance of node deployment in 2D space is illustrated in Fig. 6. A total number of 100 sensor nodes are stochastically displayed in monitoring area, including 20 beacon nodes denoted by red pentacles. Aiming to testing the performance of TWDV-Hop, comprehensive experiments are carried out in MATLAB 2016a. The experimental outcomes are contrast to DV-Hop [13], IDVLA [16], and New-IDV-Hop [18] in same simulated settings. Table 1 illustrates the simulation parameters.

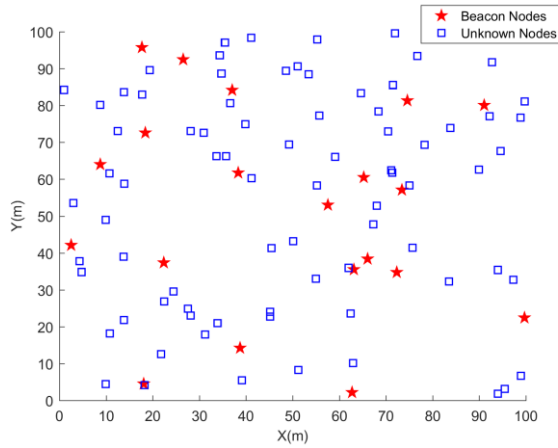


Figure 6. A typical instance of distributed nodes

TABLE I. SIMULATION PARAMETERS SETTING.

Parameters	Value
Network Area	100×100 m^2
Total Nodes	100
Beacon Nodes	20
Communication Range(m)	25

C. Experimental Results

To better examine proposed algorithm, all experiments for algorithms were performed as many as 100 times for each result, since all the sensor nodes are randomly arranged in monitoring region. We utilized the average value to evaluate improved algorithm. Here, abbreviations LE and LER are used to represent localization error, localization error radius, respectively.

- LE for Each Unknown Node

This simulation was conducted under the scenario that 100 sensor nodes were irregularly deployed in monitoring area with 20% beacon node. The communication range is 25 m.

Fig. 7 demonstrates the LE for each unknown node under four algorithms in the same environment. Obviously, our proposed algorithm (TWDV-Hop) gave the best outcomes. The LE of basic DV-Hop is around 8m and almost three times larger than TWDV-Hop. Furthermore, it has a steep polyline angle between unknown node. In contrast, all LE of TWDV-Hop are between 3m and 4m, with a flat change trend and almost close to straight line, which means the performance of TWDV-Hop is more stable. The reduction of TWDV-Hop localization error is around at 65%, 45% and 30%, respectively, when came to compared with DV-Hop [13], IDVLA [16], and New-IDV-Hop [18].

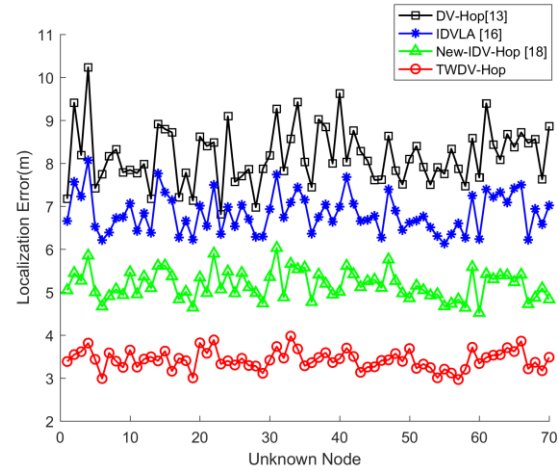


Figure 7. The LE for each unknown node

TABLE II. THE COMPARISONS OF LOCALIZATION ERROR AND STANDARD DEVIATION.

Localization Algorithm	Max. LE(m)	Min. LE(m)	Avg. LE(m)	Std. (LE)
DV-Hop [13]	10.2362	6.8131	8.1779	0.6752
IDV-Hop [16]	8.0688	6.1309	6.8358	0.4554
New-IDV-Hop [18]	6.0286	4.5171	6.0286	0.3348
TWDV-Hop	3.9753	2.9654	3.4257	0.2229

Table 2 illustrates the comparisons of LE and its standard deviation under four localization algorithms. Upon comparing with the other three localization algorithms, TWDV-Hop yielded the lowest location error in terms of max, min, and average values. The maximum LE is less than 4m and minimum LE is smaller than 3m. The average LE of TWDV-hop is decreased 59.40%, 49.89% and 33.71, compared with DV-Hop [13], IDVLA [16] and New-IDV-Hop [18], respectively. Besides, the TWDV-Hop also recorded the lowest standard deviation, which indicated that TWDV-Hop had better stability.

- Accuracy Metrics with Variation Factors

Accuracy is most significant evaluate factor for localization algorithm. In this study, LER is adopted to assess the accuracy under affected factor in terms of the number of sensor nodes, beacon node density, and communication radius.

(1) Effect of Total Number of Nodes

The total amount sensor nodes are evenly increased from 50 to 350, steady increased by 50. The communication range is 25m, and beacon nodes density is fixed at 10%. Fig. 8 and Table 3 list the experiential results of LER.

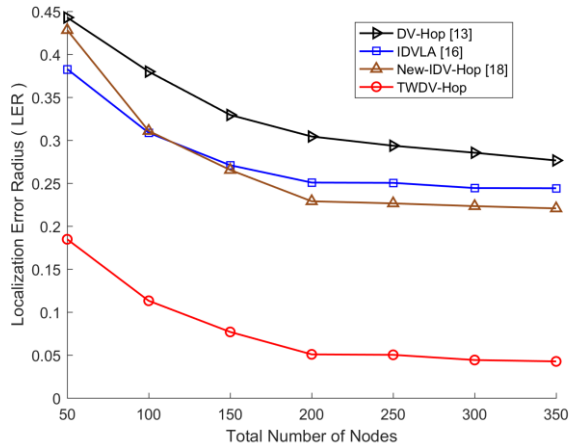


Figure 8. The LER under various total number of nodes.

Fig.8 illustrates the LER under various amounts of sensor nodes. It shows down-ward trend with sensor node increased under four algorithms. The proposed algorithm always scored the lowest error radius under all situations, especially when the nodes exceeded 150. The LER of the proposed algorithm decreased by 75%, 60%, and 70%, when compared with DV-Hop [13], IDVLA [16], and New-IDV-Hop [18], respectively.

TABLE III. COMPARISON LER OF ALGORITHMS WITH VARIOUS TOTAL NUMBER OF NODES.

Localization Algorithm	Localization Error Radius (LER)		
	Max.	Min.	Avg.
	DV-Hop [13]	0.4429	0.2765
IDLVA [16]	0.3828	0.2443	0.2789
New-IDV-Hop [18]	0.4282	0.2207	0.2720
TWDV-Hop	0.1848	0.0426	0.0804

Table 3 tabulates LER under different total number of nodes. As depicted in Table 3, TWDV-Hop exerted the best performance under LER. Upon comparing with the proposed algorithm, the LER under average term decreased to 75.66%, 64.87%, and 70.44% for DV-Hop [13], IDLVA [16], and New-IDV-Hop [32], respectively.

(2) Effect of Beacon Node Density

In this experiment, the beacon density is evenly increased from 10% to 40%. At the same time the total amount sensor nodes and communication range are 100 and 25 m, respectively. Fig.9 and Table 4 present the empirical findings under diverse beacon node density.

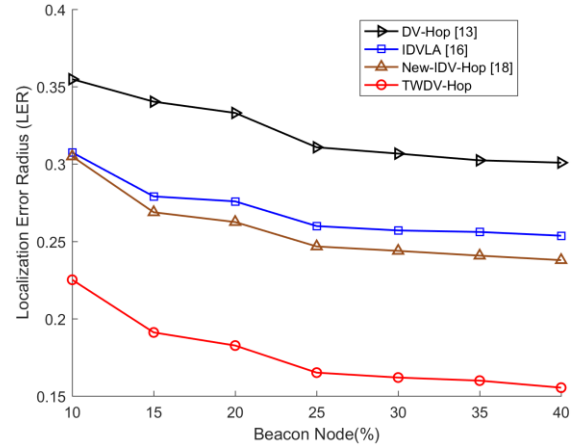


Figure 9. The LER under various beacon nodes density

Fig. 9 displays the LER with variation in beacon node density. The proposed algorithm always scored the lowest LER under all situations, especially when the beacon node exceeded 32. The LER of the proposed algorithm decreased to 45%, 35%, and 30%, when compared with DV-Hop [13], IDVLA [16], and New-IDV-Hop [18], respectively.

TABLE IV. COMPARISON LER OF VARIOUS ALGORITHMS WITH BEACON NODE DENSITY.

Localization Algorithm	Localization Error Radius (LER)		
	Max.	Min.	Avg.
	DV-Hop [13]	0.3588	0.3043
IDLVA [16]	0.3110	0.2565	0.2729
New-IDV-Hop [18]	0.3084	0.2405	0.2608
TWDV-Hop	0.2309	0.1594	0.1819

As depicted in Table 4, the proposed algorithm TWDV-Hop outperformed the rest under LER, with the average accuracy reaching up to 85%. The LA, under average term of the proposed algorithm, decreased by 44.01%, 33.35%, and 30.25%, when compared with DV-Hop [13], IDVLA [16], and New-IDV-Hop [32], respectively.

(3) Effect of Communication Range

The communication radius is increased from 20 to 36 m, while whole sensor nodes and beacon nodes are fixed at 100 and 20, respectively. Fig.10 and Table 5 tabulate the empirical outcomes of LER under different communication range.

Fig.10 reflects the LER with variation in communication range. The TWDV-Hop always scored the lowest LER under all situations. The LER of the



proposed algorithm TWDV-Hop decreased to 40%, 30%, and 20%, when compared with DV-Hop [13], IDVLA [16], and New-IDV-Hop [18], respectively.

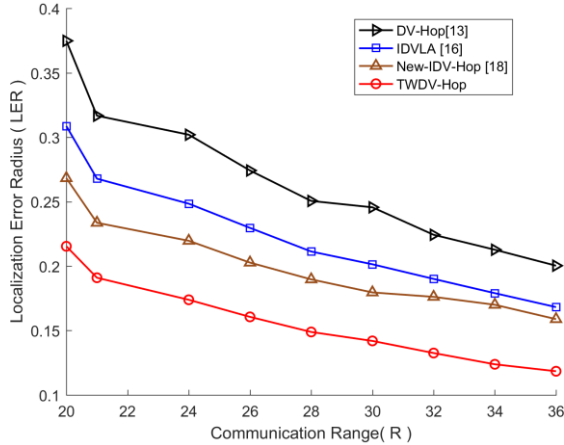


Figure 10. The LER under various communication range

As depicted in Table 5, the proposed algorithm gave the best performance under LER. When compared with the proposed algorithm, the LER, under average term,

decreased to 41.42%, 29.85%, and 21.81%, when compared with DV-Hop [10], IDVLA [16], and New-DV-Hop [18], respectively.

TABLE V. COMPARISON LER OF VARIOUS ALGORITHMS WITH COMMUNICATION RANGE.

Localization Algorithm	Localization Error Radius (LER)		
	Max.	Min.	Avg.
DV-Hop [13]	0.3748	0.2003	0.2668
IDVLA [16]	0.3087	0.2228	0.1682
New-IDV-Hop [18]	0.2683	0.1589	0.1999
TWDV-Hop	0.2154	0.1184	0.1563

• Energy Consumption Cost

Here, we adopted total number of transmitted and received packets (TTRP) to evaluate energy consumption cost, cause more than half of power spent on packet transmission. Table 6 illustrated the TTRP for four algorithms, where N is all total number of sensor nodes, m is the amount of beacon nodes and P is average network connectivity.

TABLE VI. ENERGY COST UNDER ALL ALGORITHMS

Packets		Localization Algorithms			
BP: broadcast packets		DV-Hop [13]	IDVLA [16]	New-DV-Hop [18]	TWDV-Hop
RP: received packets					
TP: Total packets					
Step 1	BP	$N \times m$	$N \times m$	$N \times m$	$N \times m$
	RP	$(N-1) \times m \times P_{avg}$	$(N-1) \times m \times P_{avg}$	$(N-1) \times m \times P_{avg}$	$1/3 \times (N-1) \times m \times P_{avg}$
	TP	$N \times m + (N-1) \times m \times P_{avg}$	$N \times m + (N-1) \times m \times P_{avg}$	$N \times m + (N-1) \times m \times P_{avg}$	$N \times m + 1/3 \times (N-1) \times m \times P_{avg}$
Step 2	BP	N	N	N	N
	RP	$N-m$	$N-m$	$N-m$	$N-m$
	TP	$2N-m$	$2N-m$	$2N-m$	$2N-m$
TTRP		$N \times m + (N-1) \times m \times P_{avg} + 2N-m$	$N \times m + (N-1) \times m \times P_{avg} + 2N-m$	$N \times m + (N-1) \times m \times P_{avg} + 2N-m$	$N \times m + 1/3 \times (N-1) \times m \times P_{avg} + 2N-m$

In first phase, beacon node broadcasts information packets to all nodes. The DV-Hop [13], IDVLA [16] and New-IDV-Hop [18] are based on flood protocol, hence three of them consumed same energy in **Step 1**. In contrast, TWDV-Hop will cut out the hop value that is larger than 3. In Section 4.1, we conducted the conclusion only one third node is one hop. Accordingly, the whole received packets are reduced one third in **Step 1**. In **Step 2**, each unknown node only forwards the first received AHS, so the communication cost of four algorithms is equal.

Overall, it can be revealed that TWDV-Hop achieved fabulous outcomes form Table 6, which consumed less energy than other three algorithms.

7. CONCLUSION

Node location technology is a research hotspot in current wireless sensor networks area. DV-hop as the most popular range-free localization algorithm for its simplicity, no range-based hardware requirement and easy to implement. However, it has lower localization accuracy



and inaccuracy AHS. Since the accurate AHS is the main reason that led to large location error. We adopted an improved method named as TWDV-Hop to address this issue. Considerable experiments are conducted to analyze the distributed law between hop count and AHS error. If the hop value is larger than three, it will be cut out to optimize AHS based on experiment result. This will greatly save energy consumption since larger hop count is discarded, not continue forward to neighbor node in broadcasting process. Furthermore, weighted matrix is added to rectify error as a result of least squares method. Not only accuracy metric but also energy consumption is taken account into to evaluate the performance proposed TWDV-Hop algorithm with various effected factor in terms of beacon node density, communication range etc. Simulation outcomes shown TWDV-Hop has superior advantages in localization accuracy with lesser communication cost. The localization error radius is decreased more 75%, compared with the traditional one. Besides, the average localization error is far smaller than 3.5m and minimum value is lower than 3, which can satisfy location-based application at some extent. We are considering extend our work under 3D WSNs in the further.

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