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RESEARCH ARTICLE

Optimized Range-Free Localization Scheme Using Autonomous Groups Particles Swarm Optimization for Anisotropic Wireless Sensor Networks

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ABSTRACT Location information is a required concern for localization-based service application in the field of wireless sensor networks (WSNs). Distance Vector-Hop (DV-Hop) algorithm as the most typical range-free localization scheme is more suitable for large-scaled WSNs. Its localization performance is good in even distributed networks. However, it demonstrated extremely poor accuracy under anisotropic networks, which is an urgent problem that need to be addressed. Accordingly, an optimized DV-Hop localization algorithm is put forward in this study with considering several anisotropic factors. Accumulated hop size error and collinearity are two main reasons that led to low accuracy and poor stability. Hence, hop size error of anchors is reduced by introducing distance gap based on anchors. Besides, weighted least square method is adopted to replace the least square method to against anisotropic factors caused by irregular radio patterns. Moreover, an Autonomous Groups Particles Swarm Optimization (AGPSO) is employed to further optimize the obtained coordinate in the first round. It developed a novel method to determine localization coverage. The localization coverage is also added to be one evaluation metric in our study, which makes up for the lack of this evaluation indicator in most of the studies. Simulation results display good localization accuracy and strong stability under anisotropic networks. In addition, it also concluded that metaheuristic optimization algorithm and weighted least square method are more suitable to conquer anisotropic factor. It briefly points out a new direction for the future research work in the localization area under anisotropic networks.

INDEX TERMS Wireless sensor networks (WSNs), range-free localization scheme, particles swarm optimization (PSO), distance-vector hop (DV-Hop), anchor node, least square method.

I. INTRODUCTION

Advanced micro-electronic technology has fostered the high-speed development of Wireless sensor networks (WSNs). It is like a sharp sword, especially, catching on the fast train of the Internet of Things (IoT). The WSNs play a bridge role in connecting the physical and digital worlds, which is composed of numerous self-organizing, tiny size, battery equipped, and limited computational sensor nodes. The sensor nodes are manually or drone-assisted distributed in the interested area [1]. Accordingly, numerous location-based applications in the field of WSNs have been widely adopted to various area, such as military, agriculture, industrial, and medical care etc [2]. A disaster location management system

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based on WSNs is developed to monitor natural disaster and rescue injured people, which largely reduced economic loss and death [3]. The natural disaster is a serious threat to the entire world, it not only caused physical death but also economic lost. On average, it caused 60,000 people deaths each year and $268 billion has lost only in the year 2020 [4]. Another typical example of location-based wireless technology is used to track positive Covid-19 contacts and analyses the potential risks with the help of IoT and big data. It not only largely suppressed the spread of the virus but also played an important role in controlling the virus [5]. Figure 1 presents the conception of typical location-based application in wireless sensor networks. When the event happened, the first thing we need to know is where, especially for the emergency events need to take quick action. Hence, how to obtain the location information accurately and promptly, and how to get the location data energy-efficiently is a key problem that needs to be solved urgently.

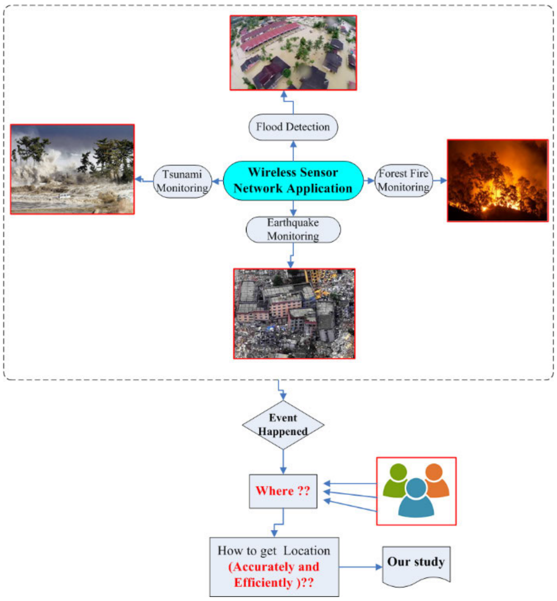

FIGURE 1. The typical location-based application in wireless sensor networks.

The precise information about location data can be obtained by attached Global Positioning System (GPS) on each sensor nodes, and it is the easiest method to get location info. The sensor node that is equipped with GPS, marked as anchor node or beacon node. The characteristic of this sensor node is that its precise coordinate information is known [6]. To simple, the sensor node without knowing position information, denotes as target node or unknown node. It is well known that sensor nodes are battery attached, it has the restriction on energy consumption and size. Hence, attaching GPS on sensor node that will incontrovertibly increase hardware cost. Undoubtably, it will also consume a huge number of extra energies, then further shorten the lifetime of sensor nodes [7]. In general, WSNs is composed of thousands of sensor nodes. And it will greatly increase the hardware cost, if each node is equipped with GPS. Consequently, all of these restrict to equip GPS on all sensor nodes.

It cannot be acceptable that manually deployed all sensor nodes in a specific area to get the location information, especially under large-scale networks [8], [9]. Accordingly, it is indispensable for the target node to locate itself assisted by anchor nodes in large-scale WSNs. The problem, how to get location information, it is denoted as the terms of 'localization'. The localization schemes could be broadly grouped into range-based and range-free localization approach, depending on whether it needs to attach additional hardware device or not. The range-based localization techniques embed GPS to each sensor node. It shows considerable accuracy, however, the hardware cost is high [10]. Nonetheless, it is not only vulnerable to environmental noises but also easily affected by obstacle or coverage holes. The limitations of existing range-based localization scheme motivate an advanced range-free localization scheme of anisotropic network to be proposed.

In contrast, the range-free localization scheme only utilizes the network connectivity information and hop to locate the target nodes. Thus, it is convenient to implant and deploy. There are several classical examples of range-free localization scheme, such as Centroid [11], Approximate Point-in-triangulation Test (APIT) [12], Distance Vector-Hop (DV-Hop) [13], Bounding-box [14] etc. Studies [15], [16], and [17] had proved that DV-Hop is the easiest and simple range-free localization scheme, so we choose DV-Hop localization algorithm as our research target in this study. DV-Hop localization algorithm demonstrated favorable accuracy under evenly distributed networks, but its performance is extremely poor under random distributed networks, especially in anisotropic networks. Despite the existing variations of DV-Hop localization algorithm have increased the localization accuracy to a certain degree, but most of them at cost of high communication overhead, computational complexity, or even at expense of increasing anchor node density. Besides, most research work without considering the complex anisotropic factors in the actual deployment. Our study introduced an optimized DV-Hop localization algorithm based on Autonomous Groups Particles Swarm Optimization (AGPSO) to tackle these issues. The principal contributions of this study are as follows.

1. A novel method based on error gap between anchors is introduced to optimize hope size to further reduce accumulated error caused by anisotropic factors.

2. It adopted an improved method to determine whether three anchor nodes are collinear or not, which greatly reduced localization error.

3. It developed an advanced method to determine localization coverage of target nodes.

4. Weighted least square method is employed to instead of least square method to against anisotropic factors.

5. An enhanced swarm-based optimization method, Autonomous Groups Particles Swarm Optimization (AGPSO) is employed to further optimize the position that obtained in the first round.

6. Besides, several performance metrics in terms of accuracy, stability, hardware cost, and communication overhead are examined under extensive experiments.

The remaining part of our study is arranged as follows. Previous works on enhanced range-free localization scheme is elaborated in Section Two. Section Three presents the basic localization process of DV-Hop algorithm, and illustrates Particles Swarm Optimization algorithm (PSO) and AGPSO, it also explains the error analysis of DV-Hop algorithm. How to converted localization problem into optimization problem is described in Section Four, our proposed localization algorithm (WDV-Hop-AGPSO) is also introduced in Section Four. Experimental results and conclusion are illustrated in Section Five, and Six, respectively.

II. RELATED WORKS

For a given wireless sensor networks S, it is assumed that there is a certain function mapping, $f_p : R_{2d} \rightarrow R$ that describes the mapping from the geographic locations (X_i, X_j) to the measured by proximity p_{ij} for each pair of sensor nodes, here the distance is denoted as $p_{ij} = f_p(X_i, X_j)$. If the mapping $f_p(X_i, X_j)$ is equals to the Euclidean distance between X_i and X_j, that means the attenuation of the signal in all directions is exactly the same, then, it is marked as isotropic networks. Otherwise, it is anisotropic networks [12]. Generally, the difference between anisotropic networks and isotropic networks is that it has characteristics that varies according to the measurement direction. The characteristics are caused by many factors such as the irregular geographic shape area, uneven node densities, and irregular radio patterns, etc. For such networks, it is said to be anisotropic network [18]. The anisotropic wireless sensor networks have three main properties based on radio irregularity, anisotropy, continuous change, and heterogeneity. In anisotropic networks, the radio signal from the transmitter has different path losses in different directions for irregular geographic shape area, this posed a new challenge to the localization algorithm, Degree of Irregularity (DOI) is a factor that adopted to measure the impact of shadowing and fading on the communication range of sensor nodes in the real-world communication environment, which expressed as the probability that two arbitrary nodes with a distance establish direct communication with each other. Besides, differences in hardware property and battery status lead to different signal sending powers, hence it fosters different received signal strengths, that further increased the difficulty of localization algorithm. Figure 2 is a typical example of DOI [19].

An abundant upgraded localization methods have been suggested in recent research work to address above-described issue. These variations of localization scheme are divided into three classifications, as depicted in Figure 3. In paper [20], hop count is quantized by distance signal, which refined the hop to decimal number. A curve fitting method is replaced the traditional method to calculate hop size. The author introduced hop count to double correct hop size [21]. The problem in indoor localization is solved by adopting single marginal antenna with assisted virtual radars [22]. Shi and Peng [23] employed the Received Signal Strength Indicator (RSSI) technology to refine hop and then adopted Quasi-Newton method to optimize the final position. Two variations are introduced in study [24], which adopted least-square method and single quadratic equation. To address the issue of strict synchronization localization algorithm, a simplifying method based on two synchronized nodes are introduced to indoor localization system [25]. An enhanced Chan algorithm is applied in hybrid RSSI and Time Difference Of Arrival (TDOA) localization model to obtain the position of target sensor nodes for its merit of stability and efficiency [26]. Two PSO-based optimized methods, Ensemble learning particle swarm optimization (ELPSO) and Ensemble learning particle swarm optimization (PSO-BPNN) are offered to further improve the localization accuracy.

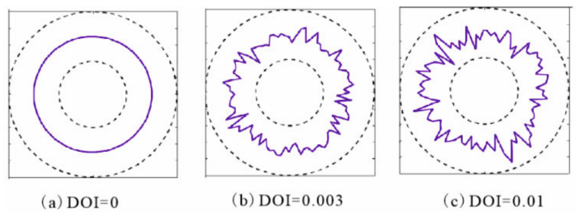

FIGURE 2. The typical DOI in wireless sensor networks.

Most of the above proposed localization schemes [21], [22], [24] demonstrates good under isotropic networks. However, most not fit to anisotropic networks. DV-Hop has poor performance especially in anisotropic networks. A locally weighted linear regression (LWLR-DV-hop) method [27] is introduced to address the hop count issue. Theorical experiments is introduced to analysis location error caused by hop count. Hence, the kernel parameter k is adopted to decide weighted matrix to weight neighbor anchor nodes, which is based on the threshold of hop count. The LWLR-DV-hop shows outstanding performance in localization accuracy under simulation and physical experiment, in terms of X-shaped, O-shaped, and L-shaped irregular topology. However, it did not involve collinearity issue and consider communication overhead. In study [28], the geometric constraint-based selection strategy is adopted to identify three classifications of anchor pair. Here, mathematic derived method is employed to calculate corresponding estimate distance for optimal anchor pair. The average hop size is for sub-optimal anchor pair to get estimate distance. Furthermore, it cannot employ LAPCD scheme to locate target node with unavailable anchor pair. Yet, some target nodes cannot be located even the accuracy increased to a certain degree. An enhanced Multi-dimensional scaling (MDS)-based method is proposed to against the anisotropic factors [29]. The proximity-distance map (PDM) is introduced to mitigate the distance error between geographic distance and measured distance. In paper [30], Voronoi diagram is adopted to optimize hop size and hop count of anchor node for anisotropic wireless sensor networks. Besides, the concept of Normalized Collinearity is

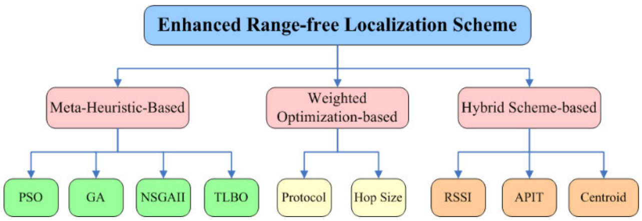

FIGURE 3. The classifications of enhanced range-free localization scheme.

introduced that is used to select a suitable set of anchor node for target node to be located. Moreover, corresponding weight based on normalized collinearity value is employed to correct target node position.

Metaheuristic algorithm is a hot research area to solve optimization problem, several represented algorithms are introduced to deal with localization problem in DV-Hop algorithm. A new improved DV-Hop algorithm for localization based on PSO is proposed in reference [31]. It developed a new mathematical model for employment of intelligent swarm algorithm. Bacterial Foraging Optimization (BFO) was introduced to boost the localization accuracy in the third phrase [32]. Four accurate variations of DV-Hop algorithm are proposed in study [33]. The first variation WDV-Hop aimed to optimize hop size by adopting weighted matrix. To further optimize the final position, the second variation HWDV-Hop employed the Two-dimensional (2D) hyperbolic location technique. The PSO algorithm is applied in WDV-Hop and HWDV-Hop by adding one extra phase to promote localization accuracy. To overcome the low localization accuracy caused by heterogeneity and anisotropy, an Harris Hawks Optimization based localization with Area (HHO-AM) localization method is proposed in paper [34]. Firstly, it divided neighbor node into two sets according to different ranges in heterogeneity networks, incoming and outgoing sets. Secondly, area minimization method is adopted to narrow reachable area. Thirdly, the localization issue is transformed into optimization problem, Harris Hawks Optimization (HHO) is employed to obtain location within reachable area using two sets. Distance-based weighted modulus between multi hop and single hop is introduced to correct the inaccurate hop size that caused by curve path. The hyperbolic localization method is taken the place of least square method to locate the position of target node. Furthermore, Chicken Swarm Optimization (CSO) is adopted to further boost the accuracy of position that obtained in the first round [35].

The above upgraded DV-hop localization algorithm mainly concentrated on optimizing the average hop size in first two steps to reduce the localization error or utilizing metaheuristic algorithm to solve nonlinear equation in the third phase. The achievement is enhanced in some degree, however, most of them at cost of high energy consumption, computational complexity and extra hardware cost, especially, without considering anisotropic factors. This motivated us to propose an optimized localization algorithm to address these issues.

III. MATHDOLOGY BACKGROUND

A. BASIC DV-HOP LOCALIZATION ALGORITHM

Several similar localization algorithms are proposed by Niculescu and Nath [13]. DV-Hop is the most popular one for its simple without range information. Generally, it is consisted of three steps. Figure 4 is a typical instance of DV-Hop algorithm.

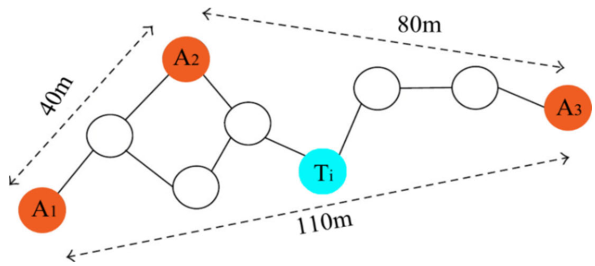

FIGURE 4. An instance of DV-Hop localization algorithm.

1) STEP1: CALCULATE MINIMUM HOP

Anchor nodes with the characters of knowing their accurate location information. Each anchor node A_i broadcasts a package table with configuration of $\{ID; (x_i, y_i), H_{ij}\}$, the initial value of H_{ij} is 0. The communicable neighbor sensor node will compare the received packet with previous one, if the hop is smaller, neighbor sensor node will update its packet table by increased one. Otherwise, the packet will be discarded. Each anchor sensor node gets its minimum hop count by this dissemination mechanism.

2) STEP 2 CALCULATE AVERAGE HOP SIZE

Individual anchor node A_i calculates its average hop size, which is given by Equation (1).

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

Here, (x_i, y_i) and (x_j, y_j) denote the coordinate of anchor node A_i and A_j. And H_{ij} represents the hop count between the two anchor nodes A_i and A_j.

After getting the average hop size, each anchor node broadcasts it by using flood protocols. The hop size from the nearest anchor node is assigned to target node. Hence, the estimate distance of target node d_{it} can be calculated by Equation (2)

$$d_{it} = AvgHopSize_i \times H_{it} \tag{2}$$

3) STEP 3 ESTIMATED THE COORDINATES OF TARGET NODES

Let (x_t, y_t) to be the coordinates of the target node t, and the following formulation can be acquired.

$$\begin{aligned} (x_t - x_1)^2 + (y_t - y_1)^2 &= d_{1t}^2 \\ (x_t - x_2)^2 + (y_t - y_2)^2 &= d_{2t}^2 \\ &\vdots \\ (x_t - x_n)^2 + (y_t - y_n)^2 &= d_{nt}^2 \end{aligned} \tag{3}$$

Each equation was subtracted from the last equation since the first one. Equation (3) can be expressed as (4), shown at the bottom of the page.

Equation (4) can be formulated as AX=B.

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

$$B = \begin{bmatrix} d_1^2 - d_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ d_2^2 - d_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 \\ . \\ . \\ d_{n-1}^2 - d_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 \end{bmatrix} \tag{6}$$

$$X = \begin{bmatrix} x_t \\ y_t \end{bmatrix} \tag{7}$$

The (x_t, y_t) can be obtained by Equation (8)

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

Here, if A^T and A are not invertible, it means the communicable anchor nodes are collinear, the target node cannot get its coordinates in this case.

B. PARTICLE SWARM OPTIMIZATION

The idea of particle swarm optimization originates from the research of bird flock's foraging behavior [36]. Each particle only has two attributes, speed, and position. Speed represents the speed of movement, and position denotes the position after movement. Each particle individually hunts for the optimal solution in the search space. And records it as the current individual optimal value, P_{best}. It is shared with other particles in the entire particle swarm, and further find the best individual extreme value as the current global optimal solution of the entire particle swarm, G_{best}. All particles in the particle swarm adjust their speed and position according to the current individual extreme value P_{best} and the shared current global optimal value G_{best}. The main idea of PSO is relatively simple, which is divided by four steps.

Step 1: Randomly initialize the speed and position of particle swarm, setting the group size.

Step 2: Calculate the value of fitness function.

Step 3: Find out individual extreme value, P_{best}.

Step 4: Find out global extreme value, G_{best}.

Assumed that there are N particles in a D-dimensional target search space, where i^{th} particle is expressed as position in a D-dimensional vector, see as follows.

$$x_i = (x_{i1}, x_{i2}, \ldots x_{iD}), i = 1, 2, \ldots, N \tag{9}$$

The velocity vector of each particle can be denoted as the following.

$$v_i = (v_{i1}, v_{i2}, \ldots v_{iD}), i = 1, 2, \ldots, N \tag{10}$$

The optimal position searched by the i^{th} particle so far is the individual extreme value P_{best}, which is recorded as the following.

$$P_{best} = (P_{i1}, P_{i2}, \ldots P_{iD}), i = 1, 2, \ldots, N \tag{11}$$

The optimal position searched by the entire particle swarm so far, the global extreme value G_{best}, which is recorded as the follow.

$$G_{best} = (G_{i1}, G_{i2}, \ldots G_{iD}), i = 1, 2, \ldots, N \tag{12}$$

Particles update its position based on the Equations (13)-(14).

$$v_{iD}^{T+1} = \omega v_{iD}^{T} + c_1 r_1 (P_{iD}^{T} - x_{iD}^{T}) + c_2 r_2 (G_{iD}^{T} - x_{iD}^{T}) \tag{13}$$

$$x_{iD}^{T+1} = x_{iD}^{T} + v_{iD}^{T+1} \tag{14}$$

where, c_1, c_2 are learning factors, generally taken $c_1 = c_2 \in [0, 4]$. ω is the inertia weight and r_1, r_2 are uniform random numbers in range of [0,1]. The particle velocity update formulation is consist of three parts. The first part is inertial part, which represents the memory of the particle's previous speed. The second part is self-recognition part, which can be understood as the difference between the current position of the particle i and its best position distance. The last part is social experience part, which represents the information sharing and cooperation between particles, which can also be interpreted as the distance between the current position of particle i and the optimal position of the group.

C. LOCALIZATION ERROR ANALYSIS

1) ACCUMULATED ERROR BY HOP

Accumulated error caused by hop count is the main reason that led to large localization error for anisotropic networks. It assumed that the shortest path of DV-Hop algorithm is close to a straight-line distribution, which is rarely exist in actual deployment. The shortest path can be blocked by coverage hop in networks. And the hop count will largely increase between sensor nodes. Especially, it can be observed from Figure 5, the true distance between anchor node A_1 and A_5 is totally different from estimated distance under anisotropic

$$\begin{aligned} 2(x_n - x_1)x_t + 2(y_n - y_1)y_t &= d_1^2 - d_n^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ 2(x_n - x_2)x_t + 2(y_n - y_2)y_t &= d_2^2 - d_n^2 - x_2^2 + x_n^2 - y_2^2 + y_n^2 \\ &. \\ &. \\ 2(x_{n-1} - x_n)x_t + 2(y_{n-1} - y_n)y_t &= d_{n-1}^2 - d_n^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 \end{aligned} \tag{4}$$

networks. Additionally, in the third step, the distance of target nodes should be by multiplying hop count and hop size, hence, which will arouse to large distance error.

2) ERROR CAUSED BY LEAST SQUARES METHOD

It is assumed that the number of communicable anchor nodes of target node T is m, A_1 (x_1, y_1), A_2 (x_2, y_2), A_3 (x_3, y_3), A_4 (x_4, y_4), A_5 (x_5, y_5) and A_m (x_m, y_m), see as in Figure 6. The coordinate of anchor node is denoted as (x_i, y_i), $(i = 1, 2, 3, \ldots, m)$, and the coordinate of target node T is expressed as (x, y). The estimated distance between target node and anchors can be presented as follow.

$$\begin{aligned}(x_t - x_1)^2 + (y_t - y_1)^2 &= d_{1t}^2\\ (x_t - x_2)^2 + (y_t - y_2)^2 &= d_{2t}^2\\ &\cdot\\ &\cdot\\ (x_t - x_m)^2 + (y_t - y_m)^2 &= d_{nt}^2\end{aligned}\tag{15}$$

There must be error ε_i between estimated distance and actual distance. Hence, the Equation (15) can be expressed as in Equation (16).

$$\begin{aligned}d_1 - \varepsilon_1 \le \sqrt{(x - x_1)^2 + (y - y_1)^2} \le d_1 + \varepsilon_1\\ d_2 - \varepsilon_2 \le \sqrt{(x - x_2)^2 + (y - y_2)^2} \le d_2 + \varepsilon_2\\ \cdot\\ \cdot\\ d_m - \varepsilon_m \le \sqrt{(x - x_m)^2 + (y - y_m)^2} \le d_m + \varepsilon_m\end{aligned}\tag{16}$$

The nonlinear equation problem, Equation (4) is transformed into a linear equation problem by the least square method. Accordingly, there must be an error caused by least squares method. It is worth emphasizing that if three communicable anchor nodes are collinear, the least square method has no solution. It means the target node cannot be located.

D. AUTONOMOUS GROUPS PARTICLES SWARM OPTIMIZATION (AGPSO)

Although PSO has the characteristics of fast convergence in the early stage, it also has disadvantages such as low accuracy and easy divergence. If the acceleration constant, maximum speed and other parameters are too large, the particle swarm will miss the optimal solution and convergence. In the later stage, as all the particles tend to the optimal solution direction, which caused the convergence speed significantly slow down. Moreover, when the algorithm converges to a certain accuracy, the optimization cannot be continued. Therefore, many scholars are dedicated to improving the performance of the PSO algorithm. Accordingly, Autonomous Groups Particles Swarm Optimization (AGPSO) based on mathematical model is introduced in study [37].

The concept of autonomous groups is inspired by the diversity of individuals in groups. It is adopted to diverse particles groups to further adjust the acceleration constant c_1, c_2 of PSO algorithm. It defined four groups for updating strategies to balance the local and global search space. The dynamic coefficients of AGPSO are illustrated in Table 1.

Here, t is the current iteration, and T represents the maximum number of iterations. The pseudo code of AGPSO algorithm is displayed in Figure 7.

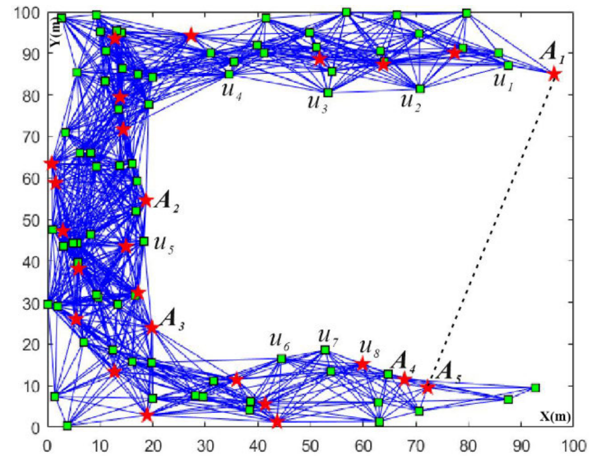

FIGURE 5. The node distribution model in anisotropic networks.

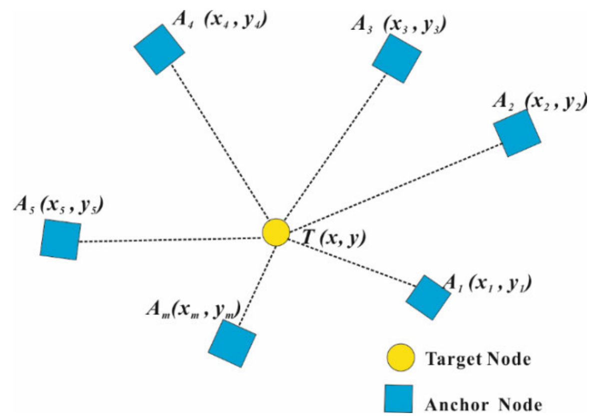

FIGURE 6. The communicable anchors around target nodes.

TABLE 1. The updating strategies of acceleration constant c_1 and c_2.

ALGORITHM		UPDATE FORMULATION	
		C_1	C_2
AGPSO	GROUP1	$1.95 - 2t^{\frac{1}{3}}/T^{\frac{1}{3}}$	$2t^{\frac{1}{3}}/T^{\frac{1}{3}} + 0.05$
	GROUP2	$\left(-2t^3/T^3\right) + 2.5$	$\left(2t^3/T^3\right) + 0.5$
	GROUP3	$1.95 - 2t^{\frac{1}{3}}/T^{\frac{1}{3}}$	$\left(2t^3/T^3\right) + 0.5$
	GROUP4	$\left(-2t^3/T^3\right) + 2.5$	$2t^{\frac{1}{3}}/T^{\frac{1}{3}} + 0.05$

IV. PROPOSED ALGORITHM WDV-HOP-AGPSO

We followed the localization process of basic DV-Hop algorithm itself to optimize its performance. It optimized the accuracy of DV-Hop algorithm from four aspects. Optimize hop size by balancing hop count, recorrect hop size for target node, calculate the coordinate of target node by weighted least square method, and reoptimize the obtained coordinate by AGPSO algorithm.

A. OPTIMIZE HOP SIZE

The inaccurate hop size error of anchor node is the main reason that caused to accumulated error. So, it is essential to correct hop size to further reduce localization error. Chen et al. [38] proposed avrage value of hop size to take place of closest hop size, which is illustrated in Equation (17). The experimental results shows that localization error went down around 10%-15%.

$$HopSize_{avg} = \sum_{i=1}^{n} HopSize_i/_n \tag{17}$$

The hop size is nearly equal to communication radius under ideal scenario. So, we adopted the error gap between estimated distance and actual distance to optimize hop size. Here, (x_i, y_i) and (x_j, y_j) is the coordinate of anchor node A_i and A_j. The larger error e_{ij} reveals the bigger deviation between the actual path and the shortest path from i and j. To reduce individual differences, the sum of all e_{ij} is employed to modify hop size in Equation (19). Accordingly, the new hop size is represented as in Equation (21).

$$e_{ij} = \sum\nolimits_{i \neq j}^{n} |\sqrt{(x_i - x_j)^2 + (x_i - x_j)^2} - Rh_{ij}| \tag{18}$$

$$\omega_{ij} = \frac{e_{ij}}{\sum_{i \neq j}^{m} e_{ij}} \tag{19}$$

$$HopSize_i' = \sum\nolimits_{i \neq j}^{m} \omega_{ij} \times HopSize_i \tag{20}$$

$$HopSize_i^{new} = HopSize_i'/_2 + HopSize_{avg}/_2 \tag{21}$$

B. RESELECT HOP SIZE FOR TARGET NODE

Studies in [17], [39], and [40] have indicated that the larger hop, the greater hop size error. Hence, we adopted the reciprocal hop to reselect hop size for the target node, not choosing the closest anchor node' hop size. The reselected hop size for target node is calculated by Equation (22-23).

$$\lambda_i = \frac{\frac{1}{h_i}}{\sum_{k=1}^{m} \frac{1}{h_k}} \tag{22}$$

$$HopSize_u = \sum\nolimits_{i=1}^{n} \lambda_i HopSize_i \tag{23}$$

C. WEIGHTED LEAST SQUARE METHOD

An optimal weighted least square is employed to against irregular networks topology [41]. Accordingly, we introduced this method to anisotropic networks. It adopted a weighted coefficient matrix W in the linear equation.

$$W = \begin{bmatrix} W_1 & 0 & 0 & 0 \\ 0 & W_2 & 0 & 0 \\ . & . & . & . \\ . & . & . & . \\ 0 & 0 & 0 & W_k \end{bmatrix} \tag{24}$$

where, $W_k = 1/H_k^4$, H_k^4 is the hop between target node T and anchor node A. Hence, Equation (8) can be converted into Equation (25).

$$X = (A^T W^T WA)^{-1} A^T W^T WB \tag{25}$$

```
Begin
Set population size N, D, T, c1, and c2
Initialize the swarm population position Xi (i = 1, 2, ..., N) and Velocity
Divide particles randomly into autonomous groups
Calculate the fitness function for each particle of swarm, {F(Xi), i = 1, 2, ..., N}, set
Pbest= inf, Gbest=min(F(Xi))
 While (t < T) do
 Calculate particles' fitness, Gbest, and Pbest
       for i =1 to N do
            for j =1 to D do
                 Adopted update strategy in Table 1 to update c1 and c2
                 Use c1 and c2 to update velocities in equation (13)
                 Update the position of the current particle by equation (14)
            End for
       End for
       t=t+1
   End while
 End
```

FIGURE 7. The pseudo code of AGPSO algorithm.

As previous mentioned, if three communicable anchor node is collinear, the Equation (25) has no solution. How to determine the collinearity is an essential problem. Here, we determine whether the triangle area is zero to judge collinearity, see as in Equation (26).

$$s = \frac{1}{2} \begin{vmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_3 & y_3 & 1 \end{vmatrix} \tag{26}$$

Studied in [42], [43], and [44] have indicated that the localization error is quite large even the three points are not strictly collinear. So, the condition of collinearity is express in Equation (27).

$$s = \begin{cases} 0 or \leq 5, collinearity \\ else, non\ collinearity \end{cases} \tag{27}$$

D. FORMULATE LOCALIZATION PROBLEM

It can be seen from the Equation (15) that the localization problem can be transformed into optimized mathematical problems to find minimum value as below.

$$f(x, y) = Min \frac{1}{m} \sum\nolimits_{i=1,2,\ldots m}^{m} \left| \sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i \right|^2 \tag{28}$$

where, $f(x, y)$ is the fitness value of (x, y), (x_i, y_i) is coordinate of target node i. And d_i is the estimated distance between target node t and anchor node i. Here, it employed the AGPSO algorithm to further optimize the obtained coordinate of target node in the first round.

The workflow of our proposed algorithm, WDV-Hop-AGPSO is illustrated in Figure 8.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Aimed at verifying the capability of our advanced localization algorithm, WDV-Hop-AGPSO, it is simulated in MATLAB 2016a. It compared with the several latest localization algorithms, PSODV-Hop [31], RRADV-Hop [8]. For anisotropic factor, it considered irregular transmit model, *DOI* model.

A typical example of random topology network is demonstrated in Figure 9, in which the whole sensor node is 100, including 20 anchor nodes and 80 target nodes. The parameters setting of compared localization algorithm in our experiment are illustrated in Table 2.

To analysis the relationship between iterations and fitness value, follow experiment is conducted with parameter setting in Table 2. This experiment is under random network topology. The iterations of DV-Hop-AGPSO and DV-Hop-PSO algorithm is illustrated in Figure 10.

It can be seen from Figure 10 that DV-Hop-AGPSO has faster convergence speed, comparing with DV-Hop-PSO. This also directly reflected the performance of AGPSO algorithm is better than PSO algorithm. The AGPSO algorithm reaches to convergence when the number of iterations is about 25. Therefore, the maximum iteration of DV-Hop-AGPSO localization algorithm is set to be 25.

A. PERFORMANCE EVALUATION METRICS

We assessed the performance of our proposed WDV-Hop-AGPSO localization algorithm from accuracy, localization coverage, communication overhead, and hardware cost. The following is corresponding evaluation metrics.

Localization error (LE) is the error between real and estimated position of target node, is expressed as Equation (29).

$$LE = \sqrt{(x_r - x_e)^2 + (y_r - y_e)^2} \tag{29}$$

Average localization error (ALE), as its name suggests, it is the average error of the total target nodes, which is defined as Equation (30).

$$ALE = \frac{\sum_{t,a=1}^{n} \sqrt{(x_r - x_e)^2 + (y_r - y_e)^2}}{n} \tag{30}$$

The localization coverage criteria are related with node density and anchor number in a network. It is measured by Localized Node Proportion (LNP), which is defined as the proportion of successfully localized nodes to all target nodes. Here, the localization error is less than 6 meters, be considered to be localized. Therefore, it shows the proportion of target nodes that are successfully located. Accordingly, LNP can be denoted as in Equation (31)

$$LNP = \frac{n_{localized}}{N} \tag{31}$$

Communication overhead can be computed by the amount of transmitted and received packets by the sensor nodes in the whole localization process. The total number of transmitted and received packets (*TTRP*) is related to target nodes, anchor nodes and network connectivity.

Here, we adopted *LE* and *ALE* to assess the accuracy of localization algorithm. The *LNP* and *TTRP* are employed to evaluate the localization coverage and energy consumption. Anchor node density is used to measure the hardware cost.

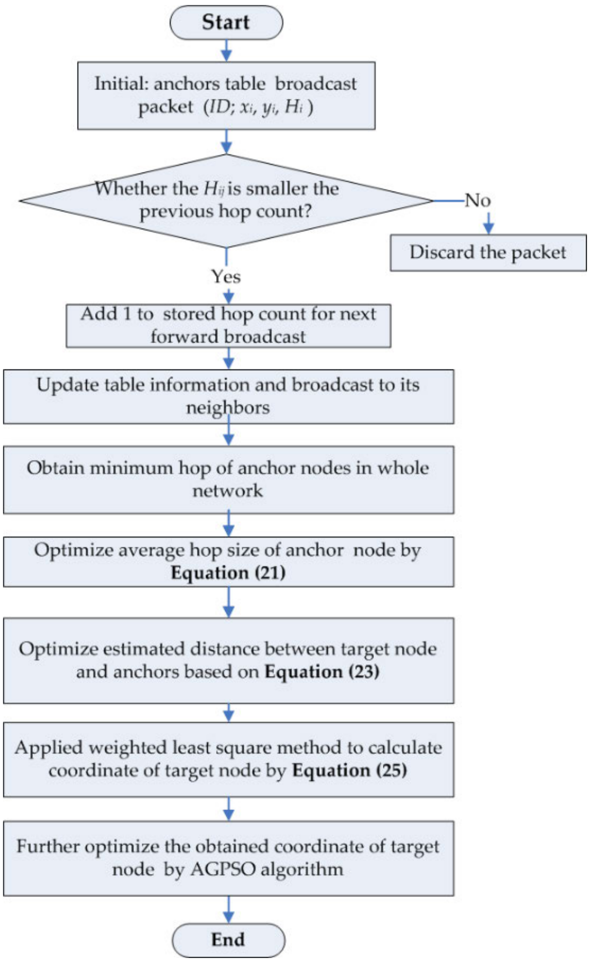

FIGURE 8. The workflow chart of WDV-Hop-AGPSO algorithm.

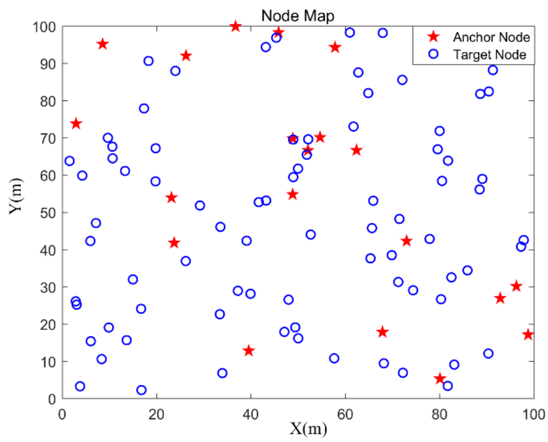

FIGURE 9. An example of random distributed networks.

B. EXPERIMENT RESULTS

1) LOCALIZATION ERROR FOR TARGET NODES

Our study is conducted under random topology network, with 100 sensor nodes. Here, the amount of anchor nodes is 20, all sensor nodes are stochastic disposed in the monitoring area. The communication radius is same, which is set to be 20m. The LE of each target node is depicted in Figure 11. And the detail LE is comprehensively shown in Table 3.

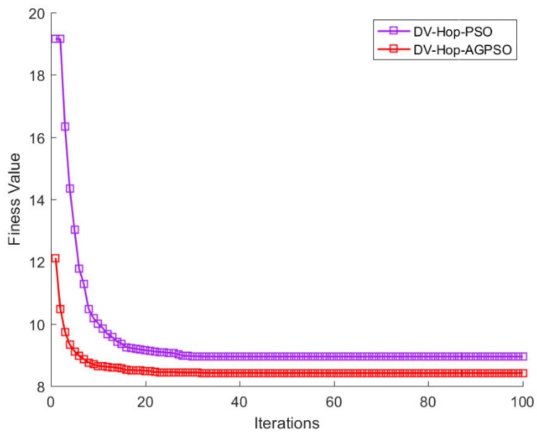

FIGURE 10. The iterations of DV-Hop-AGPSO and DV-Hop-PSO.

TABLE 2. Parameter setting for WDV-Hop-AGPSO algorithm.

	Parameters	Value
	Network size A	$100m\times100m$
	The total number of sensor nodes N	100
	The total number of anchor node m	20
	Communication Radius	20
	Degree of Irregularity (DOI)	0.01
	Transmission Model	DOI model
	Number of particles	30
	Number of iterations	25
PSO	$c_1=c_2$	2.05
	ω	0.9
	Particle's velocity V_{max}	10
RRA	The mother plants T_{pop}	10
	The relative change in the minimum value *tot*	$1e^{-2}$
	The distance of daughter plant S_{runner}	2
	The final result of local search S_{root}	$1e^{-2}$
	The selection criteria α	0.1
AGPSO	$c_1=c_2$*(initial value)*	2.0
	ω_{min}	0.4
	ω_{max}	0.9
	Particle's velocity V	(0,1)

The smaller LE, the higher accuracy. Therefore, it can be observed from Figure 11 that the accuracy performance ranking order of compared localization is WDV-Hop-AGPSO, RRADV-Hop, PSODV-Hop, and DV-Hop. The average LE of WDV-Hop-AGPSO algorithm has decreased by about 75%, 55% and 50%. It should be noted that not all target node's LE of WDV-Hop-AGPSO algorithm is the smallest one, such as No.43 target node, the localization error that obtained by the PSODV-Hop algorithm is smaller than calculated by WDV-Hop-AGPSO algorithm. The localization result of WDV-Hop-AGPSO algorithm is illustrated in Figure 12. The connection line represents the gap between the estimated coordinate and real coordinate of target node. The shorter connection line, the higher localization accuracy.

It can be seen from Table 3 that WDV-Hop-AGPSO algorithm has conducted considerable performance among all compared algorithm. Moreover, the maximum LE of WDV-Hop-AGPSO algorithm is smaller than average LE of DV-Hop algorithm. All of compared localization algorithm has a considerable accuracy under minimum LE. The average LE of WDV-Hop-AGPSO algorithm has reduced by 76.77%,

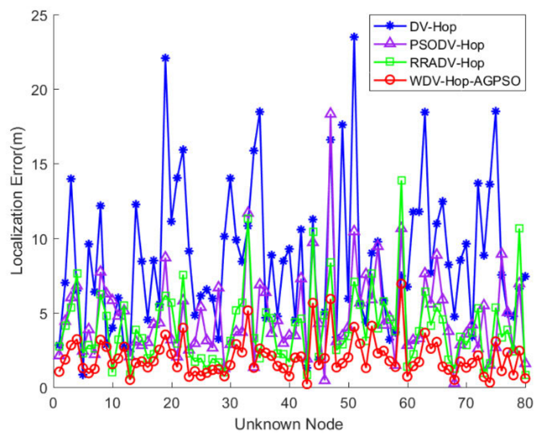

FIGURE 11. The LE of compared localization algorithm.

57.50%, and 50.01%, compared with DV-Hop, PSODV-Hop, and RRADV-Hop, respectively. And based on the minimum LE, the localization accuracy of WDV-Hop-AGPSO algorithm has reached up to 98.52%. Besides, the standard LE of compared algorithm reflects the stability of the our proposed localization algorithm. The smaller standard LE, the stronger stability.

2) EFFECT OF ANCHOR DENSITY

The anchor density will greatly affect the localization accuracy of DV-Hop algorithm based on its characteristic. The larger anchor density, the higher network connectivity. It will increase localization accuracy. Besides, anchor density reflects the hardware cost at a certain extent. Hence, we adopted the anchor density to evaluate the hardware cost of the localization algorithm. To test the effect of anchor density to localization accuracy, following experiment is executed. It is assumed that 100 sensor nodes are distributed in 100m×100m area, with communication radius 25m. The initial anchor density is 12%, it uniformly increased by 2%, and the maximum value is 30%. The ALE under different anchor density is presented in Figure 13 and Table 4.

Figure 13 shows the ALE of compared localization algorithm went down as the anchor density increased. It is consistent with the previous conclusion the higher anchor density, the higher accuracy. Because with the increase of anchor nodes, the network connectivity will increase, and the propagation path will be much smaller. This greatly reduces the number of hop errors, thereby improving the positioning accuracy. As the anchor density is higher than 16%, the ALE of our proposed WDV-Hop-AGPSO algorithm is less than 4.0m. That not only reported our proposed localization algorithm can achieve higher accuracy even under sparse anchor density, but also mirrors lower hardware cost. Furthermore, the curve of our localization algorithm changes slowly, which also embodies the superior stability.

It can be noticed that the ALE of WDV-Hop-AGPSO algorithm in Table 4 is less than 4 meters when the anchor density is larger than 14%. The ALE of WDV-Hop-AGPSO algorithm under anchor density 10% is smaller than the

TABLE 3. The detailed LE of compared localization algorithm.

Algorithm	Max. LE(m)	Avg. LE(m)	Min. LE(m)	Std. LE(m)
DV-Hop	23.4905	8.6182	0.8290	4.8716
PSODV-Hop	18.3350	4.7117	0.2579	2.9170
RRADV-Hop	13.8768	4.0058	0.8110	2.5447
WDV-Hop-AGPSO	6.9331	2.0023	0.1975	1.2775

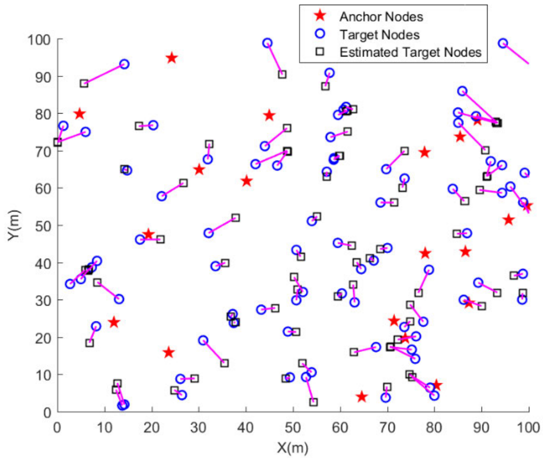

FIGURE 12. The localization error distance of WDV-Hop-AGPSO localization algorithm.

ALE of DV-Hop algorithm under anchor density 30%, which indicates the hardware cost will be save at least one third. Moreover, The ALE of WDV-Hop-AGPSO algorithm under anchor density 10% is much smaller than the ALE of both PSODV-Hop algorithm and RRADV-Hop algorithm under anchor density 30%, with reduced by 17.56% and 9.45%, respectively.

3) EFFECT OF COMMUNICATION RADIUS

The longer communication radius, the shorter best communicable path and more communicable neighbour sensor nodes. Based on this point, the communication radius will greatly affect the localization accuracy. Therefore, to investigate the effect of communication radius on WDV-Hop-AGPSO localization algorithm, following simulation experiment is carried out in this part. The communication radius R is varied from 18 m to 36 m, uniformly increased by 2m. The total number of sensor nodes are 100, including 20 anchors. Here, it also adopted ALE to appraise the accuracy of our proposed localization algorithm. The ALE under different communication radius is depicted which is shown in the Figure 14 and Table 5.

It can be observed from Figure 14, the ALE of all compared localization algorithms went down as the communication radius increased. The larger communication radius, the shorter transmit path. Hence, the minimum hop between anchors will became smaller. The ALE of RRADV-Hop has dropped dramatically, that meant it is greatly affected by communication radius. Specifically, the ALE of RRADV-Hop decreased quickly after communication radius larger than 26 meters. On the contrary, the ALE of WDV-Hop-AGPSO

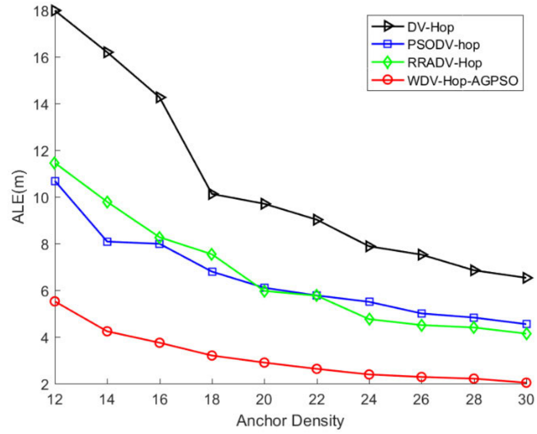

FIGURE 13. The localization error of WDV-Hop-AGPSO localization algorithm under various anchor density.

algorithm is gradually decreased, the trend is close to a straight line, indicating that it is less affected by the communication radius. Besides, the cure trend of PSODV-Hop algorithm is more stable than other compared localization algorithms

Table 5 illustrated the ALE of compared algorithm under different communication radius in random topology network. The ALE of WDV-Hop-AGPSO algorithm is not much different since communication range larger than 28 meters. The average ALE of WDV-Hop-AGPSO algorithm has reduced by 72.09%, 56.49%, and 53.88%, compared with basic DV-Hop, PSODV-Hop, and RRADV-Hop, respectively. Especially, the ALE of WDV-Hop-AGPSO algorithm is less than 1.5 meters, if the communication radis larger than 34 meters. Accordingly, the communication radius will less affect WDV-Hop-AGPSO algorithm. It can obtain better localization accuracy even under shorter communication range.

4) EFFECT OF NUMBER OF SENSOR NODES

The total numer of sensor nodes will largely affect the network connectivity to further affect the accuracy under a fixed area. To investigate the effect of the total number sensor nodes on accuracy, following experiment is conducted. The communication radius and anchor node ratio are set to be 30 meters and 20%, respectively. The total number sensor node evenly increased by 20, with initial value 60. The ALE of compared localization algorithm is illustrated in Figure 15 and Table 6.

The ALE also demonstrated drop trend as the number sensor nodes increased. The greater number of sensor nodes, the higher network connectivity. That will increase localization coverage in the localization process. Figure 15 displays the ALE of all compared localization algorithms has dropped down quickly as sensor nodes less than 80. This indicates that as the number of nodes increases, the localization accuracy gradually stabilizes. Besides, the performance of PSODV-hop algorithm is superior than RRADV-Hop algorithm when the number of sensor nodes reach up to 140.

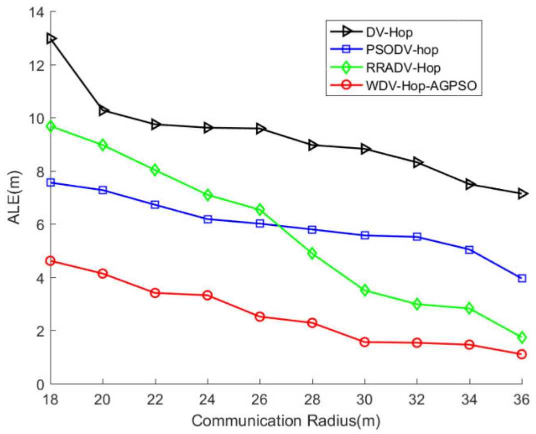

FIGURE 14. The average localization error of WDV-Hop-AGPSO localization algorithm under various communication radius.

TABLE 4. The ALE of compared localization algorithm under various anchor density.

ALE(m)	DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
A_d=12%	17.9841	10.6869	1.4547	5.5190
A_d=14%	16.1962	8.0807	9.7841	4.2348
A_d=16%	14.2635	7.9859	8.2669	3.7452
A_d=18%	10.1240	6.7930	7.5368	3.1970
A_d=20%	9.7018	6.1016	5.9661	2.8936
A_d=22%	9.0206	5.7719	5.7610	2.6254
A_d=24%	7.8787	5.4957	4.7557	2.3859
A_d=26%	7.5213	5.0008	4.2019	2.279
A_d=28%	6.8499	4.8242	4.3990	2.2063
A_d=30%	6.5270	4.5427	4.1362	2.0332

TABLE 5. The ALE of compared localization algorithm under various communication radius.

ALE(m)	DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
R=18	12.9742	7.5536	9.6812	4.6165
R=20	10.2733	7.2722	8.9683	4.1365
R=22	9.7447	6.7207	8.0267	3.4068
R=24	9.6183	6.1825	7.0959	3.3203
R=26	9.5856	6.0120	6.5330	2.5160
R=28	8.9651	5.7948	4.8876	2.2829
R=30	8.8243	5.5692	3.5034	1.5602
R=32	8.3171	5.5135	2.9853	1.5336
R=34	7.4956	5.0428	2.8232	1.4626
R=36	7.1413	3.9523	1.7417	1.1026

Table 6 displayed the ALE of four compared localization algorithm under different sensor nodes. The ALE of WDV-Hop-AGPSO algorithm is concentrated on 3.5 meters, its accuracy is less affected by the number of sensor node. It also revealed the stability of WDV-Hop-AGPSO algorithm is more roubst. The WDV-Hop-AGPSO algorithm has the best accuray, comparing with other localization algorithms. The average ALE of WDV-Hop-AGPSO algorithm has dropped by 62.69%, 39.94%, and 26.80%, compared with basic DV-Hop, PSODV-Hop, and RRADV-Hop, respectively. The second-best accuracy is RRADV-Hop algorithm, and its ALE is concentrated between range (4, 6).

TABLE 6. The ALE of compared localization algorithm under various sensor nodes.

ALE(m)	DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
N=40	13.4736	10.2856	5.9639	5.0904
N=60	12.7036	7.2799	5.1949	3.8971
N=80	9.2058	6.3017	5.0735	3.5938
N=100	9.1055	5.4775	5.0723	3.4521
N=120	8.6044	5.1925	4.9609	3.3914
N=140	8.4132	4.6686	4.8220	3.3563
N=160	8.4121	4.2240	4.5461	3.3031

5) LOCALIZATION COVERAGE FOR TARGET NODES

The localization coverage is a performance metric to evaluate the localized rate, but most research works without considering this evaluation metric. The following experiment is conducted in this section to test the localization coverage of compared localization algorithm. A total number 100 sensor nodes are stochastic distributed in monitoring area. Here, the communication radius is set to be 25 and anchor density is 30%. The statistics of localization error is smaller or equal to 6 meters as shown in the Figure 16. The localization coverage rate is displayed in Table 7. In order to show the effective localization rate more clearly, detail information of localization error range and LNP rate is illustrated in Figure 17 and Table 8.

It can be seen from Figure 16 that the order of the amount with LE not more than 6 is WDV-Hop-AGPSO, PSODV-Hop, RRADV-Hop and DV-Hop. The larger amount, the higher localization coverage rate. The localization coverage rate of WDV-Hop-AGPSO algorithm, PSODV-Hop algorithm, RRADV-Hop algorithm and DV-Hop algorithm is 97%, 41%, 70% and 31%, respectively, which is depicted in Table 8.

It can be found out from Figure 17 that most localization error of DV-Hop algorithm and RRADV-Hop algorithm are larger than 6m. The localization error of PSODV-Hop algorithm is concentrated between 2m and 6m. And the localization error of our proposed algorithm, WDV-Hop-AGPSO concentrated in interval (1,2], (2,3], and (4,5]. Here, it should be noted that the localization error distribution range of WDV-Hop-AGPSO algorithm conforms to the normal distribution, which shows that our proposed algorithm is more stable and considerable.

Table 8 explains the localization error range rate of the compared localization algorithm. It can be seen from Table 8, nearly one third localization error of WDV-Hop-AGPSO algorithm is in range (2,3]. And 21% is concentrate in (1,2] and (4,5]. And three intervals add up to 69%, which reflects our proposed algorithm has high accuracy. Except The localization error is larger than 6 meters, the localization coverage range of DV-Hop algorithm and PSODV-Hop algorithm is in (4,5], the percentage is 11% and 26%, respectively. The localization coverage range of RRADV-Hop algorithm is between 5 and 6, and the percentage is 17%. To further investigation, it found that the error between [8] and [9] is accounted around for 25%.

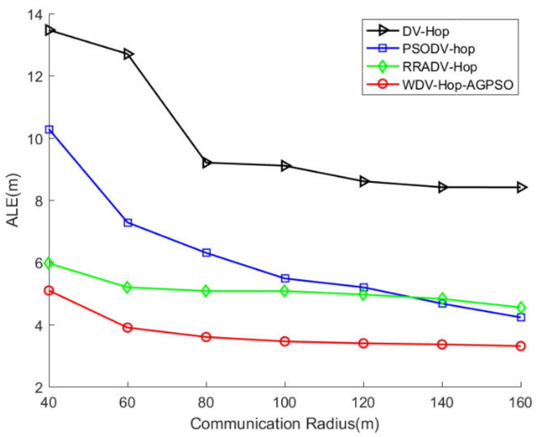

FIGURE 15. The average localization error of WDV-Hop-AGPSO localization algorithm under various number of sensor node.

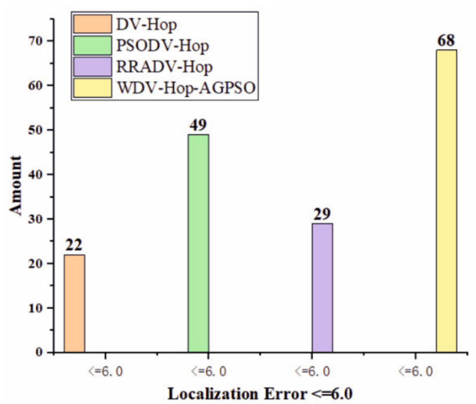

FIGURE 16. The amount of LE is smaller or equals to six.

TABLE 7. The LNP of compared localization algorithm.

LNP (%)	DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
	31%	70%	41%	97%

TABLE 8. The Localization range rate of compared localization algorithm.

LRR	DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
[0, 1]	0%	3%	0%	4%
(1,2]	0%	4%	1%	21%
(2,3]	9%	11%	9%	27%
(3,4]	7%	11%	3%	17%
(4,5]	11%	26%	11%	21%
(5,6]	4%	14%	17%	6%
(6,100]	69%	30%	59%	3%

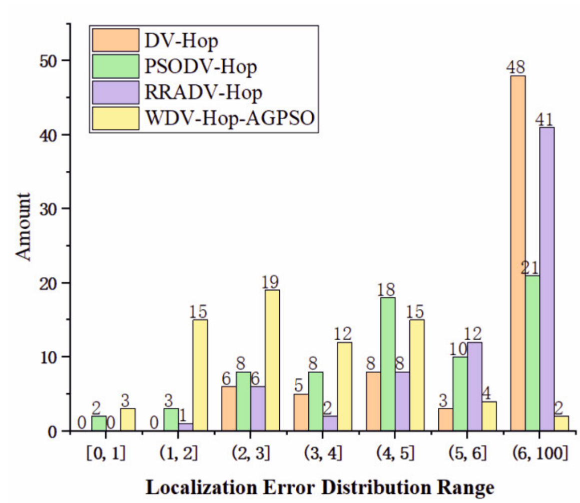

FIGURE 17. The localization error distribution range of compared algorithm.

6) COMMUNICATION OVERHEAD

The sensor nodes in the wireless sensor networks are the battery equipped, their life cycle is limited. In general, the scale of wireless sensors is relatively large, usually composed of thousands of sensor nodes, which limits the feasibility of the hardware environment to a certain extent. Therefore, communication overhead is a key indicator to evaluate the performance of localization algorithms. Here, we tested the energy consumption from the direction of theory analysis. Accordingly, it is employed the total *TTRP* to evaluate communication overhead. The *TTRP* for compared localization algorithms, DV-Hop, PSODV-hop, RRADV-Hop, and WDV-Hop-AGPSO is illustrated in Table 9. For convenience, here is a brief description of each parameter, where N, N_a, and N_t is the total number of sensor nodes, anchor nodes, and target nodes, reactively. C_{avg} is average network connectivity of the whole network. *BP* is broadcast packets; *RP* is received packets and *TP* is total packets, including transmitted and received packets.

In the first step, each anchor node transmits packet to all sensor nodes, except for itself, all nodes received the package based on flood protocol. So, in the first step the total packet of all compared localization algorithm is same. In the second step of DV-Hop algorithm, each target node only forwarded the packet from the nearest anchor nodes. The method for calculating hop size of PSODV-Hop algorithm is same as DV-Hop. Accordingly, the total packet is equal to DV-Hop algorithm. The RRADV-Hop algorithm adopts the distance error gap between anchor to remodify hop size. So, the broadcasted and received packet will be increased $N_a \times N_a$. Similarly, WDV-Hop-AGPSO also employed this method to correct hop size. In addition, it introduced hop count to assign hop size for target node, so, the broadcasted and received packet will be increased $N_t \times N_a$. In step three, all target node sends its coordinate to the nearest anchor node, thus, the total packet of compared algorithms is same. Except DV-Hop algorithm, other compared algorithms added step four to further optimize location that obtained in the first round. So, it will cost same energy as in step three. Overall, the communication overhead of WDV-Hop-AGPSO is more than DV-Hop, PSODV-Hop and RRADV-Hop. Although the energy consumption has increased compared with the other three compared algorithms. But it still within an acceptable range, comparing with the fabulous localization accuracy.

TABLE 9. The comparison of communication overhead.

Packet		DV-Hop	PSODV-Hop	RRADV-Hop	WDV-Hop-AGPSO
Step1	B_p	$N \times N_a$	$N \times N_a$	$N \times N_a$	$N \times N_a$
	R_p	$(N\text{-}1) \times N_a \times C_{avg}$	$(N\text{-}1) \times N_a \times C_{avg}$	$(N\text{-}1) \times N_a \times C_{avg}$	$(N\text{-}1) \times N_a \times C_{avg}$
	T_p	$N \times N_a + (N\text{-}1) \times N_a \times C_{avg}$	$N \times N_a + (N\text{-}1) \times N_a \times C_{avg}$	$N \times N_a + (N\text{-}1) \times N_a \times C_{avg}$	$N \times N_a + (N\text{-}1) \times N_a \times C_{avg}$
Step2	B_p	$N_t \times N_a$	$N_t \times N_a$	$N_t \times N_a + N_a \times N_a$	$N_t \times N_a + N_a \times N_a + N_t \times N_a$
	R_p	N_a	N_a	$N_a + N_a \times N_a$	$N_a + N_a \times N_a + N_t \times N_a$
	T_p	$(N_t - 1) \times N_a$	$(N_t - 1) \times N_a$	$N_a \times (N_t + 2N_a + 1)$	$N_a \times (3N_t + 2N_a + 1)$
Step3	B_p	N_t	N_t	N_t	N_t
	R_p	N_a	N_a	N_a	N_a
	T_p	$N_t + N_a$	$N_t + N_a$	$N_t + N_a$	$N_t + N_a$
Step4	B_p	--	N_t	N_t	N_t
	R_p	--	N_a	N_a	N_a
	T_p	--	$N_t + N_a$	$N_t + N_a$	$N_t + N_a$
TTRP		$N_a \times (N - 1) \times (1 + C_{avg}) + 2N$	$N_a \times (N - 1) \times (1 + C_{avg}) + 2N + 2N_t + 2N_a$	$N_a \times [\, N + (N\text{-}1) \times C_{avg} + N_t + 2N_a + 3 \,] + 2N_t$	$N_a \times [\, N + (N\text{-}1) \times C_{avg} + 3N_t + 2N_a + 3 \,] + 2N_t$

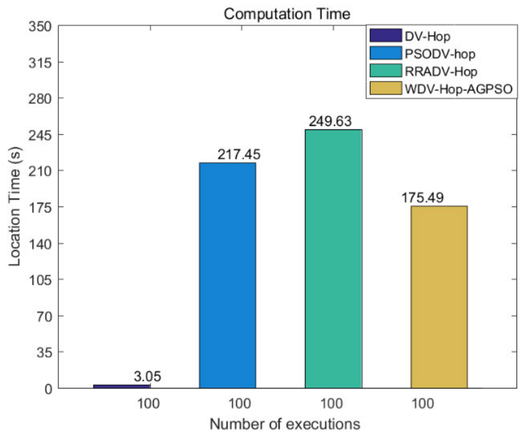

FIGURE 18. The location time of compared localization algorithm.

7) COMPUTATIONAL COMPLEXITY

The computational complexity reflected the feasibility of execution to a certain extent. The location time (LT) is adopted to evaluate the computational complexity of WDV-Hop-AGPSO localization algorithm, which is depicted in Figure 18. The experiment is carried out 100 times.

Here is the parameter setting of above conducted experiment. The total number sensor node is 100, with 25 anchor nodes. And the communication radius of sensor node is set to be 20 meters. The test environment is under Intel(R) Core (TM) i5-8300H CPU @ 2.30GHz 2.30 GHz, and 8.00 GB RAM. It can be observed from Figure 18, the LT of DV-Hop algorithm is the shortest, however, the localization accuracy is extremely poor. The LT sort order of the remaining localization algorithm is WDV-Hop-AGPSO, PSODV-Hop, and RRADV-Hop algorithm. The complexity theory analysis of localization algorithm also confirms this conclusion. Even the location time of WDV-Hop-AGPSO is much longer than the original DV-Hop algorithm. However, compared to its localization accuracy, the location time is still considerable and within an acceptable range.

Standard notions (O) of computational complexity can also be used to evaluate the algorithmic complexity, which is based on theory analysis. The Standard notions (O) of compared localization algorithm is described in Table 10. It is assumed that the anchor node is m, total number sensor node is n. The initial population of metaheuristic optimization algorithm is P, and maximum iteration is T.

TABLE 10. The Complexity of localization algorithm.

Algorithm	Step 1	Step 2	Step 3	Step 4
DV-Hop	$O(n^2)$	$O(m^2)$	$O(m^*(n\text{-}m))$	--
PSODV-Hop	$O(n^2)$	$O(m^2)$	$O(m^*(n\text{-}m))$	$O(P^*T^*(n\text{-}m))$
RRADV-Hop	$O(n^2)$	$O(m^2)$	$O(m^*(n\text{-}m))$	$O(P^*T^*(n\text{-}m))$
WDV-Hop-AGPSO	$O(n^2)$	$O(m^2)$	$O(m^*(n\text{-}m))$	$O(P^*T^*(n\text{-}m))$

In the first step, anchor node broadcasts to all communicable nodes, so all sensor nodes can obtain minimum hop. Hence, the complexity in the first step of DV-Hop, PSODV-Hop, RRAPSO-Hop, and WDV-Hop-AGPSO is $O(n^2)$. In the second step, it employed Equation (1) to calculate hop size for anchor node. Therefore, the complexity of all compared localization algorithm is same, $O(m^2)$. In step three, the target node gets its coordinate based on least square method, the complexity of DV-Hop is $O(m*(n\text{-}m))$. Similar, the weighted least square method and 2D Hyperbolic location method has the same complexity. So, the complexity of PSODV-Hop, RRAPSO-Hop, and WDV-Hop-AGPSO are also $O(m * (n\text{-}m))$. The metaheuristic optimization algorithm is adopted to further optimize location of target node. The localization process increases one phase. In that case, the complexity depends on population size and maximum iterations. So, in step four, the complexity of PSODV-Hop, RRADV-Hop, and WDV-Hop-AGPSO are $O(P * T * (n\text{-}m))$. It can be seen from Table 10, the complexity of DV-Hop localization algorithm is the simplest one, which consistent with the conclusion from the experiment results under the location time.

VI. CONCLUSION

Range-free localization algorithm demonstrates extremely poor localization accuracy in anisotropic wireless sensor networks. This study set out to explore an improved method to optimize range-free localization scheme for anisotropic wireless sensor networks, named as WDV-Hop-AGPSO. It adopted autonomous groups particles swarm optimization algorithm to further enhance the position that obtained in the first round. Besides, distance gap and weighted least square method are introduce optimize hop size and anti against anisotropic factors. The result of our proposed algorithm shows that it has a favourable localization accuracy under anisotropic networks, the high accuracy reached up to 98.52%. The main strength of the present study is that WDV-Hop-AGPSO algorithm still can obtain favourable accuracy even under sparse anchor density, less than 16%. Besides, the other strength is that the stability of our proposed algorithm is robust and strong. These findings in this study provide a new understanding of anisotropic networks. Although the study has successful demonstrated that high accuracy and strong stability, it still has certain limitations. The current research has only conducted under random network topology (e.g. C-shaped network) and 2D environment. Accordingly, more considerably work need to be done to better understand how irregular network topology affects the accuracy of localization algorithm. Further investigation and experimentation on three-dimensional (3D) networks are strongly recommended.

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