3D Many-objective DV-hop Localization Model With NSGA3

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3D Many-objective DV-hop Localization model with NSGA3

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Abstract: Wireless sensor location is a challenging task issue in the Internet of Things (IoT). Distance vector-hop (DV-hop) algorithm provides a range-free positioning scheme, but its position prediction method based on least square method brings a large positioning error. To overcome this issue, this paper constructs a three-dimensional (3D) many-objective positioning model. Specifically, we consider many factors, such as the error characteristics of the estimated distance, the distribution characteristics of nodes and the computational cost. Based on these factors, we propose a many-objective 3D-DV-hop positioning model, and propose a data preprocessing strategy and outlier removal strategy. Finally, a fashionable many-objective optimization algorithm is employed to solve the model. The experimental results show that the model proposed in this paper has great advantages in accuracy and robustness, and is superior to the current single and multi-objective positioning model.

Key Words: Data preprocessing strategy; outlier removal strategy; many-objective positioning model, 3D-DV-hop algorithm.

1. Introduction

With the rapid emergence of next generation (5G) [1-3] communication technology, some new features have emerged in wireless communications, such as small delay, high bandwidth, low energy consumption, etc. It promotes the development of some new technologies, such as non-orthogonal multiple access (NOMA) [4, 5] technology. Wireless sensor networks (WSNs) [6, 7], as a vital part of 5G technology and a crucial branch of the IoT [8], has once again evolved into the topical issues for researchers. At the same time, in most applications of wireless sensor networks, the location of sensor nodes plays an irreplaceable role, which naturally becomes one of the most popular and interesting discussion points.

Undoubtedly, global positioning system (GPS) is recognized as one of the best positioning systems in the world and it can provide numerous services such as military, logistics tracking. However, such services are restricted to cities, plains, etc., not applicable to mountains, tunnels, and more intricate area. Therefore, these areas need to deploy such nodes with communication, perception, and data processing for positioning. Thereinto, some nodes locations are perceptible, called the base station node (BSN); and others are unconscious, called the common node (CN). These common nodes estimate their locations by contacting the base station, which requires an efficient and intelligent algorithm to locate them.

DV-hop [9] is an emblematic and cost effective positioning algorithm. It estimates the distance between a BSN and a CN based on multi-hop forwarding mechanism, and locates the location by least square method. This

method realizes low-cost deployment without being sensitive to complex terrain. However, its rough positioning method also brings large positioning error. Consequently, various improved strategies and methods are emerged by scholar, including increasing weights [10, 11], employing intelligent optimization algorithms [12, 13], and improving positioning model [14, 15], etc.

Kim [16] proposed the scalable DV-hop localization algorithm with constrained multilateration to reduce higher communication cost. In 2013, Kumar [17] presented an advanced DV-hop algorithm, which enhances the positioning accuracy of nodes by weighted least squares method without increasing the computational cost. Gui [18] locates the CN by selecting the nearest anchor, and selecting the best three anchors to ameliorate accuracy. Cui [19] developed a oriented cuckoo search (CS) algorithm with weighted DV-hop algorithm. Commonly, in traditional DV-hop algorithm, the distance obtained from the hop-count between mobile nodes is discrete, which is also a factor affecting the accuracy. Therefore, Cui [20] corrected the distance by using the number of single-hop nodes shared between adjacent nodes to make the distance more precise and continuous. Gui [21] uses the difference between the actual connectivity and estimated connectivity between nodes to construct the location model, and approximately transforms it into a convex optimization model for solution.

In addition, scholars also use the DV-hop algorithm to solve the problem of sensor nodes in three-dimensional space. Chen [22] proposed use the weighted particle swarm optimization (PSO) to ameliorate localization precision. And to decrease the problem of high positioning error in 2-D and 3-D WSNs, Kaur [23] developed a weighted Grey-Wolf optimization to address DV-hop positioning model. Moreover, Sharma [24] proposed a distributed DV-hop positioning algorithm in 3D WSNs, it enhances the precision of the estimated distance by correcting the distance per hop of the anchor node. Finally, this paper used genetic algorithms to evaluate the model to further perfect accuracy.

In contrast, this paper comprehensively considers the influence of weights and estimated distance on the positioning accuracy of nodes, and proposes a many-objective 3D-DV-hop positioning model with NSGA3, NSGA3-3DDV-hop. The remainder of this paper is organized as follows. Section II introduced existing multi-objective positioning algorithms in 2D and 3D WSNs and motivation and contributions in this paper. In section III, the positioning model based on DV-hop is introduced. And many-objective 3D DV-hop localization model with NSGA3 is presented in part IV. Finally, simulation and analysis are evaluated in part V, and this work is concluded in part VI.

2. Related work and contribution

In last decade, multi-objective [25, 26] optimization algorithms are mushrooming in industrial [27-29] and informatics domains. Similarly, these algorithms are also used in WSNs. In 2017, Shahzad [30] regarded the minimum number of hops and minimum time cost as the two objectives, and performed it on various anisotropic networks and achieved good results. Wang [31] analyzed the characteristics of sensor communication in WSNs, and proposed a multi-objective DV-hop localization algorithm based on theoretical distance in 2D networks. Compare with single-objective positioning model, its performance has been significantly improved. Wang [14] explored the error distribution between estimated and practical distance in sensor nodes, and ameliorated the multi-objective localization model by using Gaussian error correction. Moreover, multi-objective optimization algorithms are also used in sensor node localization in three-dimensional space [15, 32]. This model is based on practical average distance per hop not theoretical distance, which can effectively reduce the sensitivity of the algorithm on the positioning accuracy of anisotropic networks.

However, the existing models have the following issues. 1) Model limitation: the factors affecting the positioning performance include estimated distance, weight and error distribution. However, the existing positioning models only contain one or two influencing factors. It results in inaccurate positioning accuracy. 2) Computational cost: in the existing positioning algorithms based on intelligent optimization, the initial value of the

population is generally randomly generated, which leads to a slow convergence speed. 3) Outlier interference. Not all estimated distances between anchor nodes and unknown nodes will improve the positioning performance. On the contrary, some estimated distances will bring noise, and corresponding anchor nodes are outliers. Such as Fig. 1, BSN_i denotes the base station node, d_i denotes the corresponding estimated distance between a common node and BSN_i. As shown in Figure 1, the nodes detected by BSN_1. are red, and the nodes detected by other nodes are blue. In contrast, the distribution of blue points is more concentrated, and the red nodes are more divergent. This means that red nodes are more likely to be outliers.

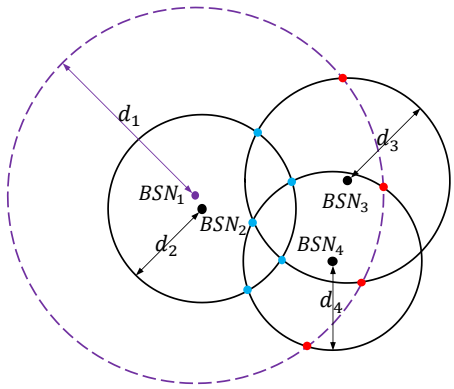


Fig. 1. Outlier detection in WSNs.

To solve these problems, we propose a many-objective positioning model and employ NSGA3 [33] to solve this model. The main innovations and contributions of this paper are as follows:

- To address the issue that the existing positioning model does not fully consider the factors affecting the positioning accuracy, we propose a many-objective positioning model. The model includes the estimated distance of anchor nodes, weight design, and the error distribution characteristics of estimated distance.
- To reduce computational cost, a data preprocessing is proposed in this paper. It accelerates the population convergence by improving the quality of the initial value of the population.
- To reduce the noise interference caused by outliers, an outlier removal strategy is designed in this paper. It makes the model insensitive to outliers and increases the robustness of the model.

3. 3D DV-hop positioning model with optimization algorithms

The DV-hop (3D) positioning algorithm consists of three processes, including broadcast, distance measurement and positioning. However, the 3rd stage of the DV-hop algorithm is usually replaced by the optimization algorithm, and the process is as follows.

1st stage: broadcast. Each BSN broadcasts packets with location and hop count to the network, and other nodes forward the packets and record the minimum hop count (which refers to the minimum hop count between nodes). It should be noted that the hop count information increases as the number of packets forwarding increases.

2nd stage: distance measurement. According to the position of the BSN and the number of hops (which between the nodes) obtained, the average distance per hop (Per_dis_i) is calculated as follows:

$$Per\_dis_i = \frac{\sum_{j \neq i} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i + z_j)^2}}{\sum_{j \neq i} hop_{ij}} \tag{1}$$

where, hop_{ij} denotes the minimum hop counts between BSN_i and BSN_j , (x_i, y_i, z_i) and (x_j, y_j, z_j) indicate

the positions of BSN_i and BSN_j .

And then, the estimated distance (d_{ik}) between BSN_i and CN_k (common node) is calculated as:

$$d_{ik} = Per\_dis_i \times hop_{ik} \tag{2}$$

where, hop_{ik} denotes the minimum hop between the BSN_i and CN_k .

3rd stage: positioning. In this stage, because the least squares method has large positioning errors, scholars use various optimization algorithms to replace it. And the positioning model is as follows:

$$F_{1k} = \sum_{i=1}^{n} \left| \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2} - d_{ik} \right| \tag{3}$$

where, F_{1k} denotes the traditional objective function, n denotes the number of BSNs, (x_k, y_k, z_k) denotes the estimated position of CN_k , d_{ik} denotes estimated distance between BSN_i and CN_k .

Apparently, the positioning precision of the model is determined by the estimated distance (d_{ik}), and since the terrain of the node deployment has a large impact on Per_dis_i , the estimated distance (d_{ik}) is unstable. In order to reduce the sensitivity to d_{ik} , Cai [15] proposed the second objective function, as follows:

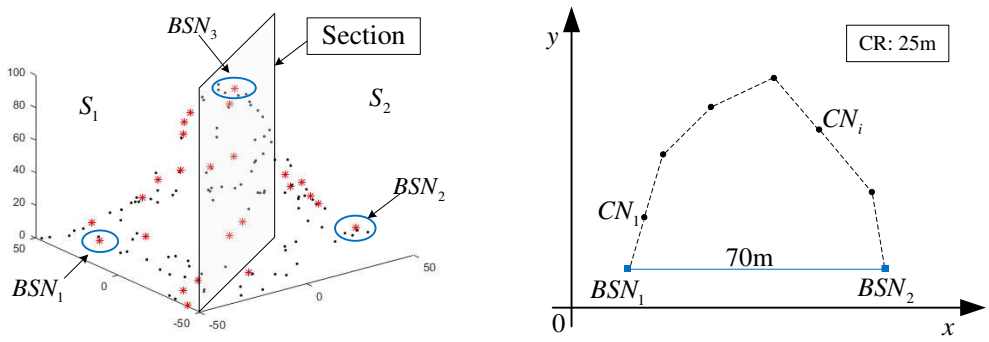
$$F_{2k} = \sum_{i=1}^{n} \left| \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2} - dis_{ik} \right| \tag{4}$$

where, dis_{ik} is calculated by Eq. (5) and (6).

$$Per\_avgdis = \frac{\sum_{i=1,2,\ldots,n} Per\_dis_i}{n} \tag{5}$$

$$dis_{ik} = Per\_avgdis \times h_{ik} \tag{6}$$

Fig. 2 shows the distribution of nodes with peak topography and its sectional view. In Fig.2 (a), the sensor nodes (the number is 130) are following uniformly distribution in this area, which contain the base station nodes (BSNs, the number is 30) and common nodes (CNs). And we assume that Fig. 2 (b) is the sectional view in the Fig. 2 (a) (where the blue nodes are defined as BSNs, called BSN_1 and BSN_2 , the other nodes are defined as CNs, called CN_i , and *CR* denotes the communication radius, and the value is 25m).



(a) (b)

Fig. 2. The distribution of nodes with peak topography and its sectional view. (a): the nodes distribution; (b): the sectional view.

From Fig. 2 (b), we can know that the distance between BSN_1 and BSN_2 is 70m, and the CR is 25m. Ideally, it requires two intermediate nodes to implement communication between BSN_1 and BSN_2. However, the actual situation requires multiple nodes to carry out the communication, such as BSN_1 and BSN_2 in Fig. 2 (b). According to the node distribution of Fig. 2 (a), Table 1 can be obtained.

Table 1. Outlier detection analysis

Per_avgdis (m)		dis (m)		error (m)	
average distance	14.5848	estimated distance	102.0936	estimated errors	32.0936
confidence interval	[13.92, 15.25]	confidence distance interval	[97.44, 106.74]	confidence error interval	[27.44, 36.74]

Table 1 shows the results of the average distance (Per_avgdis), estimated distance and estimated errors. And we noticed that the value of lower bound of confidence error interval is larger than CR (25m). Emphatically, in literature [14], Wang find that in normal circumstances, the maximum estimated error value is CR. Therefore, we can know that for node (BSN_2), node (BSN_1) is an outlier. More generally, when the node is placed on the opposite side of the peak, the probability that the BSN is an outlier will increase. Unfortunately, the existing method is helpless for solving this problem. To effectively deal with this problem, this paper presents a many-objective positioning model and outlier removal strategy to optimize CNs.

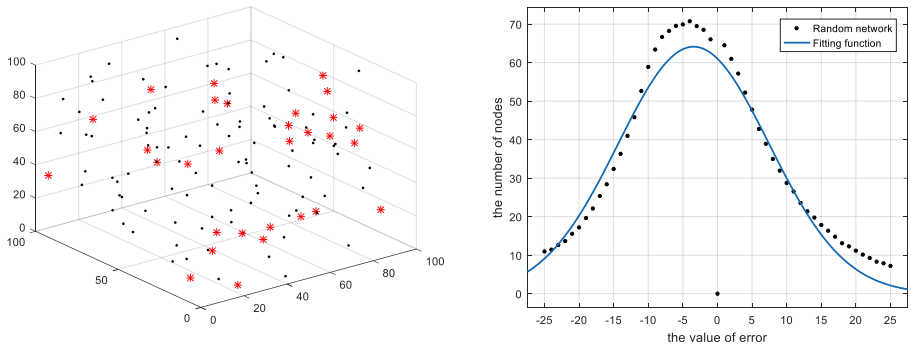
4. Many-objective model and 3D DV-hop NSGA3 algorithm

4.1 Data preprocessing strategy

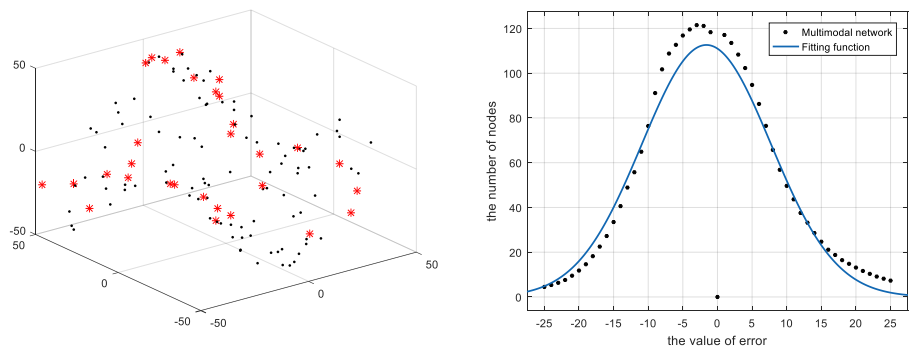
Data preprocessing is frequently used in industrial manufacture, especially in data mining and image processing. And in the positioning of WSNs, in order to reduce the time consumption of the algorithm, scholars usually choose the algorithm with fast convergence to solve the model. However, this approach breaks the balance between convergence speed and ability. Therefore, to reduce the time cost and ensure the convergence ability of the

algorithm, a data preprocessing strategy is proposed in this paper.

In 2019, Wang [14] found that in the 2D region, the error between the estimated and actual distance is following Gaussian distribution. According to this finding, an assumption can be obtained, which is, if the error of the 3D region is also following the Gaussian distribution, this conclusion (where, the conclusion represents the error follows Gaussian distribution) can improve the initialization of the population. Therefore, we have statistical statistics on the error characteristics of the 3D region, and the results are shown in Fig. 3 and Table 2. Where, the number of BSN is 30, total nodes number is 130, CR is 25 and runtime is 500.



(a)



(b)

Fig. 3. The chart of error characteristic statistics. (a) Random network; (b) Multimodal network.

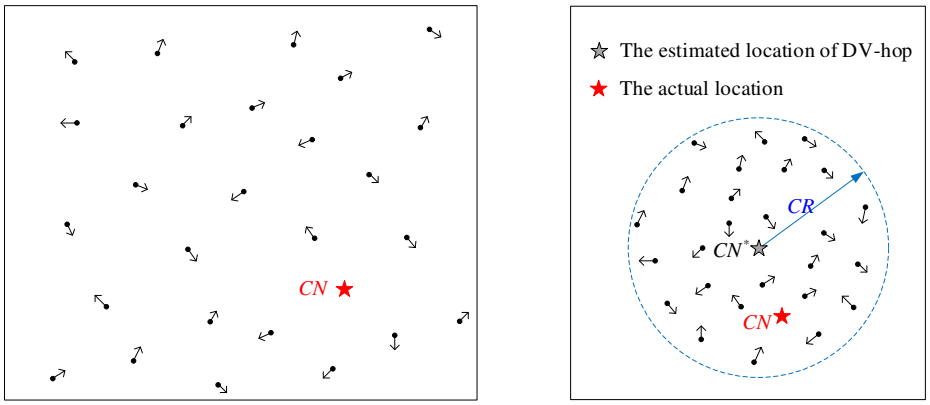
Fig. 3 shows the test sets and the error characteristics (where, the test set is one of 500 tests.). From the Fig. 3 (a) and (b), we can know that the error is consistent with expectations and is following Gaussian distribution. Table 2 shows the fitting function and relevant parameters. Obviously, in different networks, the values of μ are tending to 0, and the δ tending to $\frac{1}{3}CR$. On this basis, the DV-hop algorithm uses the least squares method to solve the position of the node, and the error characteristics of DV-hop follow this discipline.

Table 2. Fitting function and parameters

Test set	Fitting function	Parameters	Value	With 95% confidence bounds
Random network	$f_R(x) = 64.13 \cdot e^{-\left(\frac{(x+3.445)}{15.42}\right)^2}$	μ	-3.445	[-4.53, -2.36]
		δ	10.91	[9.78, 12.04]
Multimodal network	$f_M(x) = 112.6 \cdot e^{-\left(\frac{(x+1.593)}{13.18}\right)^2}$	μ	-1.593	[-2.59, -0.59]
		δ	9.32	[8.32, 10.33]

Therefore, to address the convergence problem of the algorithm, this paper proposes a data preprocessing strategy, which uses the position obtained by the DV-hop algorithm for population initialization, such as Fig. 4. In Fig. 4, (a) refers to the traditional initialization, and (b) refers to the initialization based on the DV-hop positioning result. And the pretreatment strategy refers to the initialization of the population is based on the Gaussian error

characteristics, generating Gaussian perturbation at the position estimated by DV-hop. Compared with Fig. 4 (a), the population of Fig. 4 (b) has a better initial value at initialization, which significantly increases the convergence rate of the population.



(a) (b)

Fig. 4. The comparison between traditional and DV-hop based initialization. (a) Traditional initialization; (b) DV-hop based initialization.

4.2 Outlier removal strategy

From Fig. 2 and Table 1, we can acquire that the probability that the BSN is an outlier is increased as the number of hops between it and the CN increases, which can lead to an increase in error. To reduce the interference of outliers on positioning, this paper develops an outlier removal strategy. And then, to determine the number of outliers, we performed a simulation error test on BSNs, where, the parameters are the same as in subsection 4.1, and the result is show in Fig. 5.

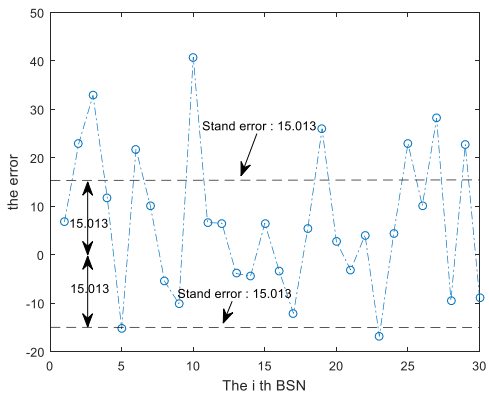


Fig. 5. Analysis of the number of outliers.

Fig. 5 shows that the error situation for each BSN. Apparently, the standard deviation of the error is 15.013, and there are 20 BSNs in the interval [-15.013, 15.013], which accounts for $2/3$ of the summary nodes. And to get the general regulation, we performed an independent repetitive simulation, and the runtime is 500. And the results show that there are averages of 18.97 BSNs in the standard deviation interval, where the number of BSNs is 30. Apparently, the ratio within the standard deviation interval is tending to $2/3$. Therefore, this paper regards nodes outside the interval as outliers, and its number accounts for $1/3$ of the total. And the removal process is shown in Algorithm 1. The removal of outliers is achieved by indexing the estimated distances, weights, and BSNs that satisfy the condition.

Algorithm 1: Outlier removal operation

1: **Begin**

2: **Input**: Number of BSNs: BN; the hop count between

```
        BSN_i and CN: hop_i ;
    Sort ( hop_i ) ascending, and record index address.
    for i=1: 2/3 · BN
      Record the index of estimated distances, containing four
        objectives.
      Record the index of weight.
      Record the index of BSNs.
    End
End
```

4.3 Many-objective Localization model

In 2019, Cai [15] developed the multi-objective DV-hop model, she took the average hop distance as the second optimization objective in the positioning model. It is worth noting that the error characteristics and weight are also important factors affecting positioning accuracy. In this paper, we present the other two objectives based on the error characteristics and weight.

According to section 3.1, we know that the error of estimated distance is roughly following the Gaussian distribution, $error: (0, \frac{1}{3}CR)$. Therefore, A Gaussian error correction is performed as follows.

$$Dis\_GE_{ik} = d_{ik} + GE_{ik} \tag{7}$$

where, Dis_GE_{ik} represents the estimated distance with the Gaussian error correction, GE_{ik} represents the Gaussian error correction between BSN_i and CN_k.

The third objective function is defined as follows:

$$F_{3k} = \sum_{i=1}^{n} \left| \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2} - Dis\_GE_{ik} \right| \tag{8}$$

Generally, there are different effects on nodes when hop counts between BSNs and CNs are not consistent. It means that an appropriate weight design will bring the gain of positioning performance. Therefore, this paper considers the weight model as one of the objectives in the construction of a many-objective model. The weight model is as follows.

$$F_{4k} = \sum_{i=1}^{n} \omega_i \left| \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2} - d_{ik} \right| \tag{9}$$

where, ω_i denotes the weight value and it is calculated as follows, which means that the weight decreases with the hop count increase.

$$\omega_i = \frac{\sum_{i=1}^{n} hop_i}{hop_i} \tag{10}$$

Consequently, the many-objective positioning model is constructed as follows.

$$F = [\sum_{k=1}^{N-n} \min(F_{1k}), \sum_{k=1}^{N-n} \min(F_{2k}), \sum_{k=1}^{N-n} \min(F_{3k}), \sum_{k=1}^{N-n} \min(F_{4k})] \tag{11}$$

4.4 Many-objective DV-hop with NSGA3

This section describes the algorithm for solving the model, NSGA3, which is developed for handling more than three objectives optimization problems in practical. In this paper, it is applied to solve the many-objective

DV-hop positioning model, and the flow chart is shown in Fig. 6. where, t represents the current iteration, P(t) denotes the parent population in the iteration t, Q(t) denotes the child population in the iteration t, R(t) represents the population before non-dominant sort. And it is continued in this paper that the reference-point-based non-dominated sorting strategy in the literature.

5. Simulation and analysis

5.1 Parameters and evaluation indicator

In this section, the parameter values of NSGA3 and 3DDV-hop are shown in Table 3. Particularly, in stand NSGA3, the value of population is 156 and maximum iteration is 500 when the objective function is 4. However, it is obvious obtained from the table 3, the number of populations and maximum iteration are much smaller than the standard NSGA3 because the data preprocessing strategy is adopted. And it can reduce computational cost distinctly.

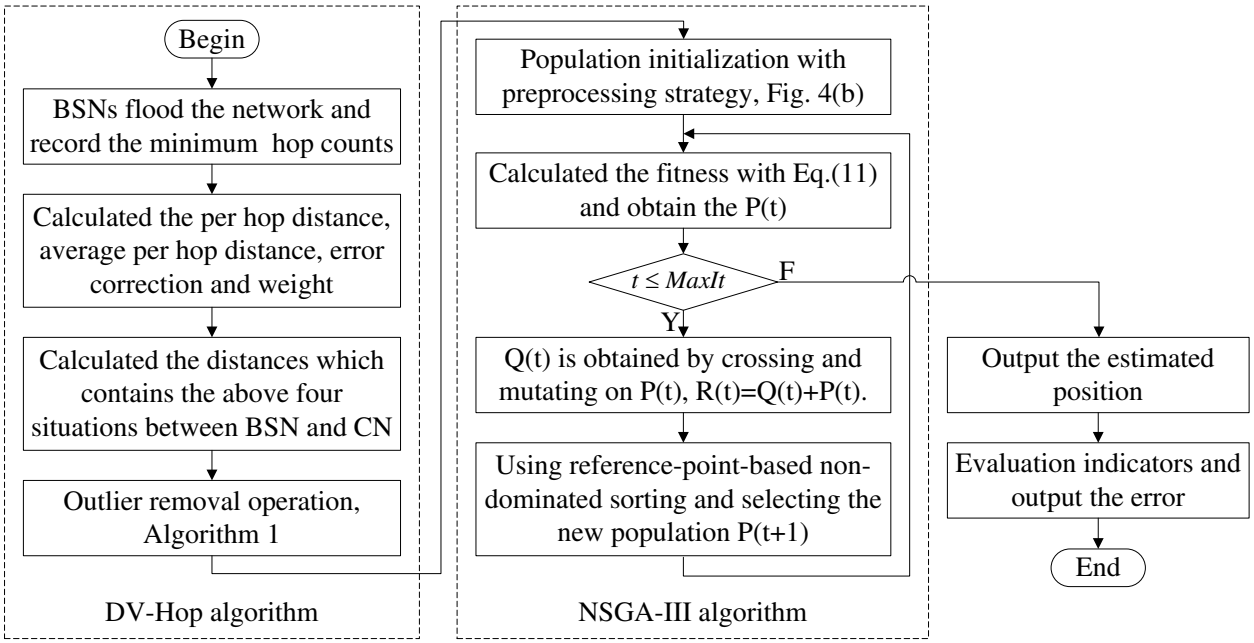


Fig. 6. The flow chart of NSGA3-DV-hop.

In addition, the test set of this paper is the same as Fig. 3, including random and multimodal network. And the evaluation indicator is as follows.

$$PE_i = \frac{1}{CR} \cdot 100\% \sqrt{(x_i^* - x_i)^2 + (y_i^* - y_i)^2 + (z_i^* - z_i)^2} \tag{12}$$

$$APE = \frac{100\%}{(N-n) \times CR} \sum_{i=1}^{N-n} \sqrt{(x_i^* - x_i)^2 + (y_i^* - y_i)^2 + (z_i^* - z_i)^2} \tag{13}$$

where, PE_i denotes the positioning errors of CN_i, APE denotes the average positioning errors of all CNs, (x_i^*, y_i^*, z_i^*) and (x_i, y_i, z_i) represent the estimated and realistic position, respectively.

Table 3. The parameter values of NSGA3 and 3DDV-hop.

NSGA3	3DDV-hop

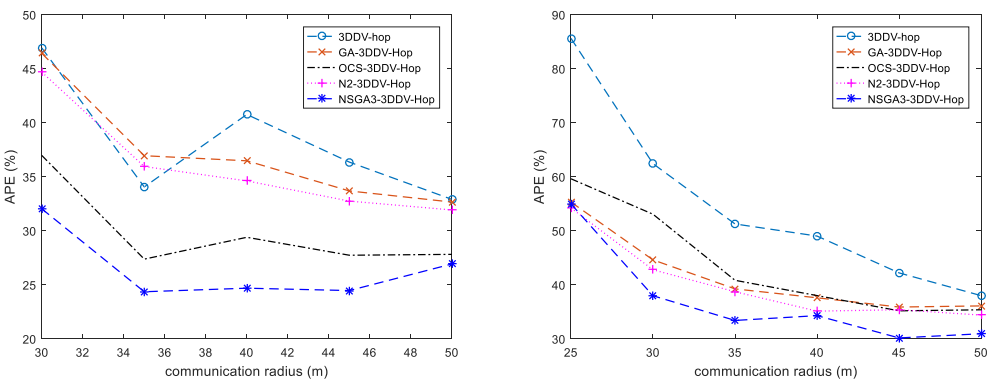
Parameter	Value	Parameter	Value
cross probability, Pc	1	Runtimes	30
mutation probability, Pm	1/d	CR (m)	30 (25-50)
Crossover operator distribution parameters	30	number of nodes, N	130 (70-130)
Variation operator distribution parameters	20	number of BSNs, n	25 (10-35)
number of populations, NP	30	——	——
maximum iteration, MaxIt	30	——	——

5.2 The APE with different CR

To test the performance of the algorithm (NSGA3-3DDV-hop), abundant simulation is executed in this section, and compare with other algorithms. Table 4 shows the variation of errors in different CRs. It is not difficult to find that the error value is ∞ when the number of nodes is 25 in the random network. The reason for this phenomenon is that there are some sensor nodes in the deployed nodes that cannot be detected by other nodes. It makes the position of some nodes impossible to calculate, so that the error tends to ∞. In Fig. 7, with the CR increases, the APE of different algorithms generally shows a downward trend. And the NSGA3-3DDV-hop not only reveals prominent precision advantages, but also has more excellent robustness than other algorithms.

Table 4. The APE of different CR.

Communication Radius		25	30	35	40	45	50
random network	DV-Hop	∞	46.92	34.05	40.76	36.35	32.90
	GA-3D-DVHop	∞	46.42	36.94	36.47	33.68	32.65
	OCS-3D-DVHop	∞	36.97	27.37	29.39	27.73	27.81
	N2-3DDV-Hop	∞	44.68	35.94	34.61	32.74	31.92
	NSGA3-3DDV-Hop	∞	**32.03**	**24.35**	**24.68**	**24.46**	**26.92**
multimodal network	DV-Hop	85.61	62.41	51.25	49.01	42.19	37.98
	GA-3D-DVHop	55.30	44.60	39.23	37.58	35.87	36.08
	OCS-3D-DVHop	59.61	53.05	40.82	37.99	35.17	35.36
	N2-3DDV-Hop	**54.21**	42.77	38.70	35.11	35.37	34.38
	NSGA3-3DDV-Hop	54.96	**37.96**	**33.39**	**34.28**	**30.15**	**30.93**



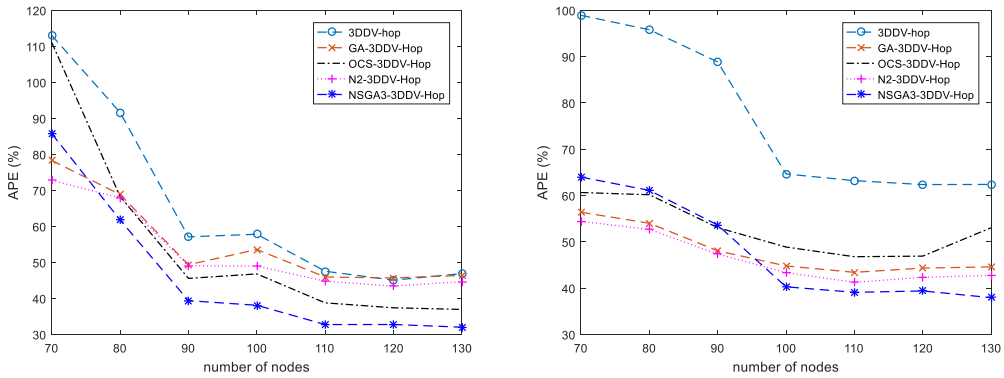
(a) (b)

Fig. 7. The APE of different CR. (a) Random network; (b) Multimodal network.

5.3 The APE with different nodes

Table 5. The APE of different nodes.

Number of nodes		70	80	90	100	110	120	130
random network	3DDV-Hop	113.07	91.66	57.12	57.84	47.57	45.09	46.92
	GA-3DDVHop	78.32	68.89	49.38	53.60	45.98	45.71	46.42
	OCS-3DDVHop	111.08	68.34	45.58	46.83	38.79	37.42	36.97
	N2-3DDV-Hop	**72.82**	67.91	49.12	48.99	44.80	43.45	44.68
	NSGA3-3DDV-Hop	85.78	**61.81**	**39.40**	**38.12**	**32.77**	**32.78**	**32.03**
multimodal network	3DDV-Hop	98.93	95.82	88.87	64.67	63.23	62.38	62.41
	GA-3DDVHop	56.41	54.03	48.08	44.81	43.43	44.35	44.60
	OCS-3DDVHop	60.66	60.19	53.09	48.89	46.80	46.93	53.05
	N2-3DDV-Hop	**54.44**	**52.69**	**47.40**	43.36	41.27	42.35	42.77
	NSGA3-3DDV-Hop	64.00	61.13	53.65	**40.30**	**39.11**	**39.41**	**37.96**



(a) (b)

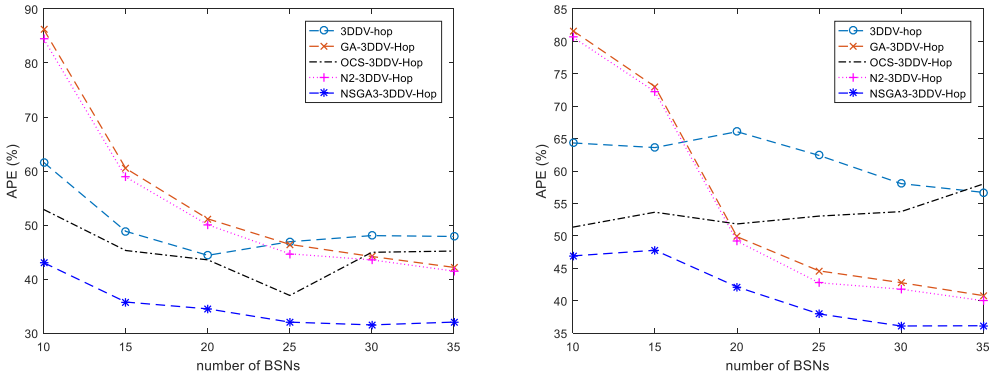
Fig. 8. The APE of different nodes. (a) Random network; (b) Multimodal network.

Table 5 and Fig. 8 shows that the APE in different nodes. NSGA3-3DDV-hop emerges huge advantage in positioning accuracy. From Fig. 8, it is obvious that the APE of NSGA3-3DDV-hop is distinctly better than single-objective model (GA-3DDV-hop and OCS-3DDV-hop) and 3DDV-hop in random network. And it has outstanding performance than other algorithms when the nodes larger than 95 in multimodal network.

5.4 The APE with different BSNs

Table 6. The APE of different BSNs.

Number of BSNs		10	15	20	25	30	35
random network	DV-Hop	61.60	48.84	44.40	46.92	48.05	47.89
	GA-3D-DVHop	86.21	60.49	51.15	46.42	44.18	42.17
	OCS-3D-DVHop	52.88	45.29	43.56	36.97	44.96	45.19
	N2-3DDV-Hop	84.44	58.88	50.05	44.68	43.55	41.48
	NSGA3-3DDV-Hop	**43.03**	**35.75**	**34.49**	**32.03**	**31.52**	**32.04**
multimodal network	DV-Hop	64.33	63.62	66.07	62.41	58.06	56.71
	GA-3D-DVHop	81.64	73.02	49.87	44.60	42.78	40.79
	OCS-3D-DVHop	51.35	53.65	51.84	53.05	53.74	57.99
	N2-3DDV-Hop	80.64	72.24	49.18	42.77	41.78	40.00
	NSGA3-3DDV-Hop	**46.91**	**47.78**	**42.13**	**37.96**	**36.10**	**36.14**



(a) (b)

Fig. 9. The APE of different BSNs. (a) Random network; (b) Multimodal network.

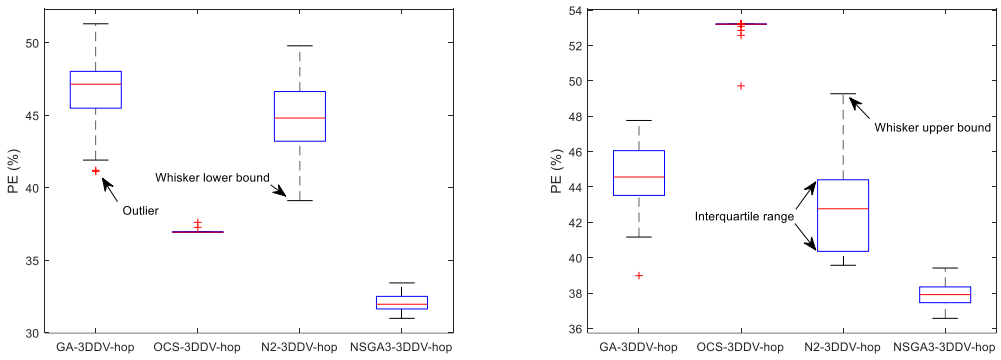
Table 6 and Fig. 9 shows that the APE with different BSNs. And we can obtain that the APE of NSGA3-3DDV-hop is always superior to other algorithms in different number of BSNs and network. That is because the outlier removal strategy (ORS) is adopted to reduce the interference of the outliers (which denotes bad BSNS) during the positioning process.

5.5 The PE and confidence error intervals

This section shows the confidence error interval and the error (PE) of the node. Fig.10 provides the error distribution boxplot of different algorithms; apparently, NSGA3-3DDV-hop has the lowest error interval in different network. To reveal its performance more clearly, this paper performs the confidence bounds analysis on simulated data. And Table 7 demonstrates the standard deviation and confidence bounds (where, the parameter settings are the same as in Table 3). In random network, the confidence bounds of NSGA3-3DDV-hop is similar to OCS-3DDV-hop, and in multimodal network, it has preeminent confidence bounds.

Table 7. The confidence bounds and standard deviation.

algorithms		GA-3DDV-hop	OCS-3DDV	N2-3DDV-hop	NSGA3-3DDV
The confidence error intervals (probably at 95%)	random network	2.462	**0.1354**	2.6908	0.6691
		[1.96, 3.31]	**[0.11, 0.18]**	[2.14, 3.61]	[0.53, 0.90]
		46.4185	36.9732	44.6766	**32.0271**
		[45.49, 47.34]	[36.92, 37.02]	[43.67, 45.68]	**[31.78, 32.28]**
	multimodal network	2.0174	**0.6444**	2.384	0.7085
		[1.60, 2.71]	**[0.51, 0.87]**	[1.89, 3.20]	[0.56, 0.95]
		44.5995	53.0505	42.7662	**37.9607**
		[43.84, 45.35]	[52.81, 53.29]	[41.87, 43.65]	**[37.70, 38.23]**

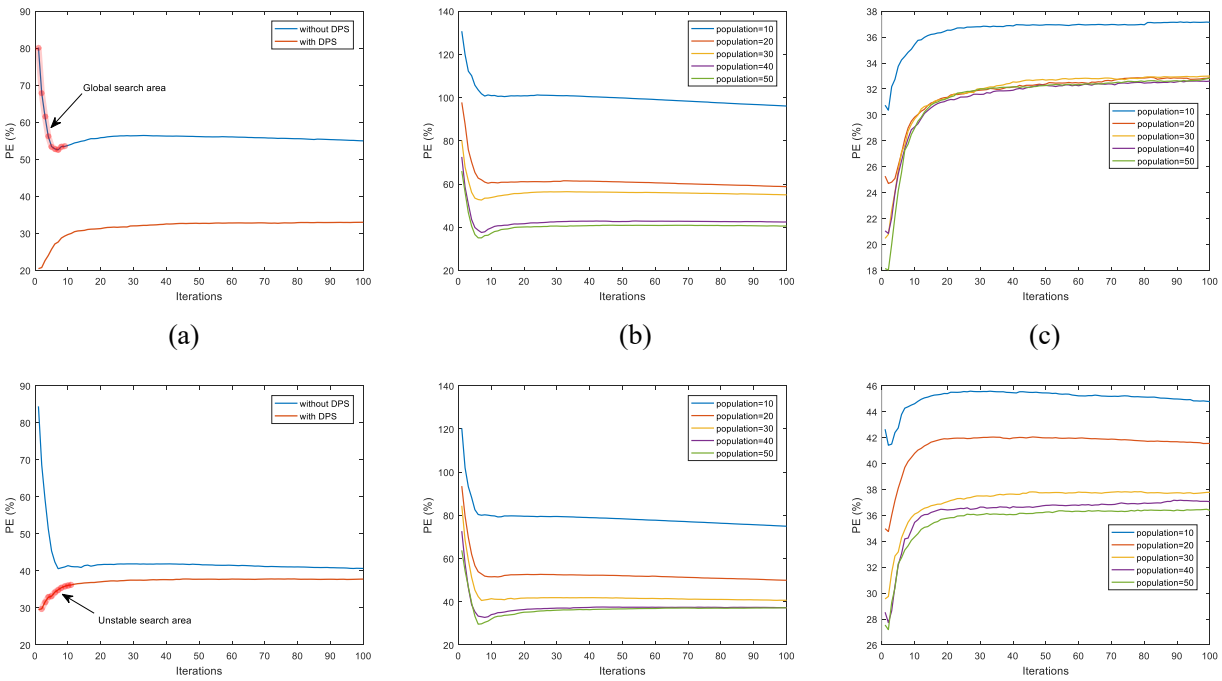


(a) (b)

Fig. 10. The PE of different algorithms. (a) Random network; (b) Multimodal network.

5.6 The convergence analysis

In order to test the validity of the data preprocessing strategy (DPS), this paper analyzes the convergence of the algorithm with and without DPS, and Fig. 11 provides the convergence curve. Obviously, we find that the NSGA3-3DDV-hop with DPS has a prominent advantage compare to the NSGA3-3DDV-hop without DPS. In Fig. 11 (a), the highlight denotes the global search area, which caused by unconscious initialization, like the Fig. 4 (a). The large search area causes a phenomenon that the initialization error is large, and then local search makes the error tend to be stable. Conversely, in Fig. 11 (b), the highlight denotes the unstable search area, which caused by purposeful initialization (DPS), like the Fig. 4 (b). And the error of DV-Hop is following Gaussian distribution; which determined that the initial population node with DPS has a higher probability of approaching the actual position. Therefore, from Fig. 11(d), when the value of iteration is 1, the NSGA3-3DDV-hop with DPS has lower error; subsequently, the error slightly increased and stabilized.



(a) (b) (c)

(d) (e) (f)

Fig. 11. The convergence curve of the algorithm. The first row is the random network and the second is the multimodal network. (a) Population=30; (b) NSGA3-3DDV-hop without DPS; (c) NSGA3-3DDV-hop with DPS; (d) Population=30; (e) NSGA3-3DDV-hop without DPS; (f) NSGA3-3DDV-hop with DPS.

Additionally, from (a)-(f), it is obvious that when the population is 30, the convergence error of NSGA3-3DDV-hop without DPS is higher than NSGA3-3DDV-hop with DPS. And when the population increases, although the positioning error is reduced, it is still inferior to NSGA3-3DDV-hop with DPS. And it which indicates that DPS plays an important role in reducing the time complexity and improving the positioning accuracy.

5.7 The time complexity

This section compares the time complexity between different algorithms (where, OB denotes the number of objectives). From Eq. (11), the algorithm optimizes the nodes not as an entirety; therefore, it can find the location of a specific node. And as an added result, it also inevitably brings high time complexity compare with the other three contrasting algorithms. However, on the one hand, due to the adoption of preprocessing strategy, the population and the maximum number of iterations are reduced, resulting in lower time complexity than NSGA-III. On the other hand, compare with existing models, NSGA3-3DDV-hop has an excellent superiority in positioning precision. Therefore, this increase in computational complexity is acceptable in practical applications.

Algorithms	time complexity
GA-3DDV-hop	$O(MaxItgNP\log NP)$
OCS-3DDV-hop	$O(MaxItg(\mathrm{N}-\mathrm{n})gNP\log NP)$
N2-3DDV-hop	$O(MaxItgOBg(NP)^2)$
NSGA3-3DDV-hop	$O(MaxItg(\mathrm{N}-\mathrm{n})gOBg(NP)^2)$

6. Conclusion

Generally, there are many elements that have a momentous impact on positioning accuracy, which contains estimated distance, computational cost, localization model and potential outliers. These influencing elements did not receive the attention of scholars during the positioning process, resulting in an inaccurate positioning accuracy. To handle these problems, this paper develops a many-objective positioning model, which considers the commonness (Per_avgdis) and individuality (Per_dis_i) of nodes, error characteristics and weight. Moreover, the data preprocessing and outlier removal strategies are adopted to speed up the convergence of the population and improve the positioning accuracy. Finally, the model is embedded in a fashionable NSGA3 many-objective optimization algorithm, i.e. NSGA3-3DDV-hop. The simulation results show that the NSGA3-3DDV-hop has prominent advantages compared with the single and multi-objective models.

In conclusion, the many-objective model has brilliant performance overall in this paper. However, there are also some shortcomings, such as Table 5. And we will analyze the reasons and optimize it with efficient strategies.

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Conflict of Interest

Penghong Wang declares that he has no conflict of interest. Hangjuan Li declares that he has no conflict of interest. Xingjuan Cai declares that she has no conflict of interest.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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