Indian Journal of Geo Marine Sciences
Vol. 51 (03), March 2022, pp. 219-228

The VF-PSO optimization algorithm for coverage and deployment of underwater wireless sensor network

Y F Hu*[,a], Y J Sun[b] & L Chen[b]

[a]School of Information and Control Engineering, Qingdao University of Technology, Qingdao, China

[b]Institute of Oceanographic Instrumentation, Qilu University of Technology (Shandong Academy of Sciences), Qingdao, China

*[E-mail: huyif12@163.com]

Received 04 April 2020; revised 29 February 2022

Coverage is a factor to reflect the network service quality of the Underwater Wireless Sensor Network (UWSN). Existing UWSN has problems of void-hole and low coverage, which is reducing UWSN lifetime and ability to monitor deployment areas. To improve network coverage and network lifetime, a coverage optimization method based on virtual force and particle swarm optimization (VF-PSO) is proposed in this article. By action of virtual force, the underwater mobile nodes would move to a better position to improve network coverage in this method. For the VF-PSO algorithm, the virtual force can guide the optimization of particles and accelerate the convergence of particles to the global optimal solution. This algorithm could not only optimize the movement trend of nodes to maximize the coverage ratio but also adjust the node distance threshold to reduce the network coverage redundancy. Simulation presents that compared with other typical algorithms, VF-PSO can improve the network connectivity and coverage of the UWSN area, and effectively avoid the network void-hole problem.

[**Keywords**: Coverage optimization, Underwater wireless sensor network, Virtual force, VF-PSO algorithm, Void-hole]

Introduction

Recently with the increasing demand for the construction of marine ranching, Underwater Wireless Sensor Network (UWSN) technology has received more and more attention. The UWSN includes a large number of underwater sensor nodes using underwater acoustic communication to form a self-organized data transmission network. To monitor some underwater areas and collect data, the UWSN must make sure that the monitored area is completely covered by the UWSN. Otherwise, if a part of the area (void-hole area) is not covered, some events that occur in this area cannot be detected[1]. However, there are some problems for UWSN to achieve 100 % coverage[2], such as inaccurate node positioning in the network, data processing delay and node communication anti-interference problems. The coverage problem reflects the monitoring ability of the UWSN area deployed by network nodes. The void-hole problem will increase the energy cost of the UWSN, so the coverage degree affects the coverage of the UWSN and the lifetime of the network[3].

The research on UWSN by foreign research institutions lasted for several years. The UWSN routing protocol has been systematically researched by the Underwater Sensor Network Laboratory of the University of Connecticut[4]. For the UWSN coverage problem, Zou *et al*.[5] introduced the Virtual Force algorithm (VF) to improve the network coverage. However, the sensors in this algorithm did not have a path planning graph for repositioning, node collision may occur when the sensors were repositioned and the positioning of multiple targets was not considered. Wang *et al*.[6] proposed a k-Equivalent Radius enhanced Virtual Force Algorithm (k-ERVFA), which realized non-uniform area coverage optimization for different k-coverage requirements. The performance comparison of the results showed that k-ERVFA had better coverage in high-k coverage sub-regions, enabling ideal diversified k-coverage deployments. For the problem of node communication connection, domestic and foreign experts and scholars have proposed several optimization algorithms[7-9]. Li *et al.*[10] proposed a discrete PSO algorithm for the problems of the UWSN clustering method. The algorithm reduced network energy costs, and improved network robustness. But the connectivity of nodes of the algorithm did not be analyzed. To sum up, the coverage optimizing method of UWSN is important to improve the performance of UWSN. The article adopts an algorithm combining virtual force and PSO to optimize the network coverage.

Model description

Perception model

This article sets the following assumptions. 1) All the nodes are deployed on the seabed 2D plane and have the same initial energy. 2) Each node has the same communication coverage area. 3) All nodes can send and receive data. A UWSN model is shown in Figure 1, and the nodes coverage area is also presented. All the sensor nodes deliver data to the sink via a multi-hop route, and then the sink would transmit data directly to the base station on the sea surface.

The coverage model of UWSN established in this article refers to the model presented by Du *et al.*[11]. The sensing radius of each node is r, and the sensing circular area is $s = \pi r^2$, S_i is the area covered by the i-th node. The centroid C_i of the i-th node is at the center of each circled area. Therefore, (x_i, y_i, r) is used to represent the sensing domain of the i-th node. $S_i \cup S_j$ is the effective area covered by the i-th node and j-th node together. $\cup_{i=1}^{N} S_i$ means the effective area covered by N nodes together. f is the effective coverage ratio of $\cup_{i=1}^{N} S_i$ to total area S_Ω, and can be used to evaluate the quality of nodes coverage[12]:

$$f = \frac{\cup_{i=1}^{N} S_i}{S_\Omega} \quad \dots (1)$$

The target of the work is to maximize the value of equation (1).

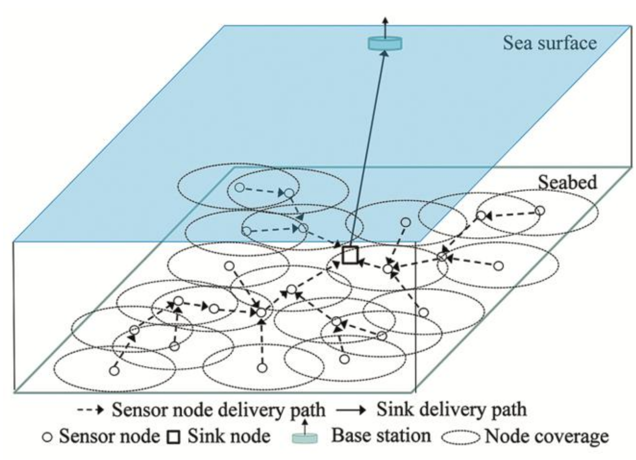

Fig. 1 — Layout and coverage diagram of underwater wireless sensor network

Node selection scheduling model

The problem of effectively planning nodes deployment should be solved. The node selection model presented by Shi[13] could reduce energy consumption. In this article, it would select some redundant nodes to sleep. During the process of the algorithm, the redundant node near a dead node would move to the location of this node to replace it. This algorithm could fill the hole of coverage caused by the node death.

According to the theorem, when the communication distance of one node is greater than 2 times the sensing distance ($R_c > 2R_s$), the perceived coverage of the network can ensure the communication coverage of the network, so under this prerequisite, the network communication connectivity could be ensured.

To satisfy the requirement of at least one-degree coverage when the network is dormant, the nodes of the network are divided into several groups. For each round, some nodes of the group are selected to transmit data, the others sleep[14]. The group ensures a high degree of aggregation, and the coverage areas of all nodes in the group are adjacent to each other so that the working nodes can effectively cover most of the sensing area of the group. Therefore, a request for each fused group is needed to make and all nodes in the two groups are in a state of covering adjacency.

Assume that there are two groups A_1 and A_2, the sensing distance of nodes is R_s. All member nodes in the two groups are connected in pairs, so the distance between node x_i in A_1 and node x_j in A_2 is less than $2R_s$ ($d(x_i, x_j) \le 2R_s$). Then the connection relationship m_{ij} between the two nodes is assumed to be $m_{ij} = 1$, otherwise, it is 0:

$$m_{ij} = \begin{cases} 1, & d(x_i,\ x_j) \le 2R_S \\ 0, & d(x_i,\ x_j) > 2R_S \end{cases} \quad \dots (2)$$

At the same time, the connectivity parameter $C_{\alpha\beta}$ between groups is defined as follows:

Suppose there are two groups A_α and A_β, where the number of nodes is S_α and S_β, the sensing distance of the nodes is R_s, any node x_i in A_α and any node x_j in A_β, so

$$C_{\alpha\beta} = \sum_{i \in A_\alpha, j \in A_\beta} \frac{m_{ij}}{S_\alpha \times S_\beta} \quad \dots (3)$$

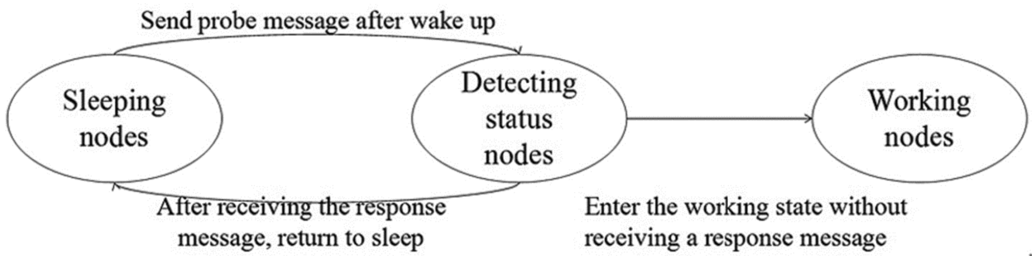

Fig. 2 — The model of node status scheduling mechanism

The model of the nodes' status scheduling mechanism is shown in Figure 2.

Covered hole repair model

The node density is adjusted by the node distance threshold D_{th}. D_{th} is set as $2R_s$ and there are "monitoring loopholes" in the monitoring environment, and areas are not within the monitoring capability of any sensor. As shown in Figure 3(b), to achieve "full coverage" of the area (any point in the monitored area is within the monitored range of at least one sensor node), the optimal deployment of the node at this time meets $d=\sqrt{3}R_s$ (ref. 15). Network coverage models with different node distance thresholds are shown in Figure 3.

According to the above analysis, it is known that the network area coverage is related to the node sensing distance R_s, and the network connectivity is related to the node communication distance R_c. To maintain network area coverage and network connectivity, the value of the node distance D_{th} threshold should be:

$$D_{th} = \begin{cases} 2R_s & R_c > 2R_s \\ \sqrt{3}R_s & \sqrt{3}R_s \le R_c \le 2R_s \\ R_c & R_c < \sqrt{3}R_s \end{cases} \quad \ldots (4)$$

If $R_c > 2R_s$, network connectivity can be maintained when the area is covered. Else, if $R_c < \sqrt{3}R_s$, coverage can be ensured when the network is connected.

Obstacle local perceptual movement model

The obstacle avoidance model of the UWSN is in its infancy, other domain models for obstacle research already exist[16]. Thus, the Ad Hoc network[17] obstacle avoidance model adapted to the characteristics of the underwater wireless sensor network is used for analysis. Because the nodes of UWSN can only

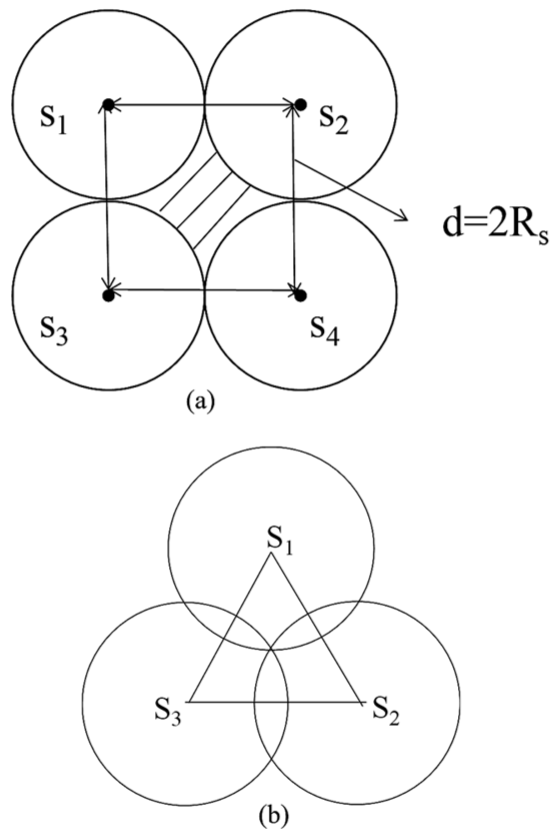

Fig. 3 — (a) Coverage holes exist ($d=2R_s$), and (b) Uncovered void ($d=\sqrt{3}R_s$)

accept information in the perceptual range[18], the global perceptual avoidance model is no longer applicable. The article adopts an Obstacle Local Perceptual Movement (OLPM) model for obstacle avoidance[19]. The obstacle avoidance model is shown in Figure 4.

The obstacle local perception movement model can be described as follow: If there is no obstacle on the line from the node to the destination in the visible range, the node will move to the target point. Until the obstacle appears, the node will choose the path to avoid the obstacle, and then continue to move towards the destination until the endpoint is reached.

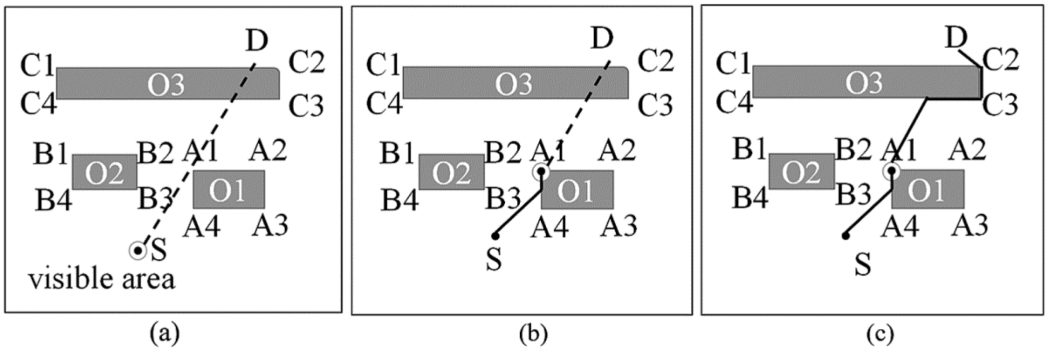

Fig. 4 — OLPM path selection

Materials and Methods

Node deployment in UWSN is relatively sparse, so some nodes are mobile. These mobile nodes can not only solve the problem of coverage holes caused by node failure due to insufficient energy but also autonomously move to the corresponding monitored area based on measured data. However, in the actual node movement process, due to the intricateness of the underwater environment, there are often some moving obstacles flooding between them, and the movement and shape of these obstacles are uncertain. In this article, the above OLPM model is used for obstacle avoidance. During the movement of the node to the target point, if there is no obstacle, the node would move directly to the destination. Else if there are obstacles on the way, the node will choose other paths to bypass the obstacles. During path selection, the length of paths is compared to find the optimal path. Every time the node moves one step forward, it performs a path selection until it finally bypasses all obstacles to reach its destination.

As shown in Figure 4(a), the node selects the OLPM route from the starting point S to the destination D. The initial state of the node is straight and obstacle O1 appears during the process of movement, then the node state will be adjusted to avoidance. Because the node can only focus on the distance of the current moving step, it will choose the path that can bypass some obstacles and make the distance shorter, which is presented in Figure 4(b, c). By comparing the length of each step, the current optimal path is obtained.

Node deployment

The problem of node deployment in UWSN could be divided into two types: sparse deployment and dense deployment[20]. For area coverage, dense deployment strategies are mainly used. In this article, according to the different node deployment densities in the monitored area, the network deployment model is non-uniform deployment.

In general, the node deployment density is determined by the communication load that the node can bear. The physical location of the aggregation node often determines the communication load of each node in the network during the data collection process. For areas with heavy loads, it is necessary to increase the deployment density of nodes. Conversely, for monitored areas with light loads, it is necessary to reduce the deployment density of nodes. The number of underwater sensor nodes will increase geometrically as the distance between sink nodes decreases[21]. The number of deployed nodes in the monitored area could be estimated by the following equation[22]:

$$N \geq ln(1-p) \div ln\left(1-\frac{\pi r^2}{S_\Omega}\times\frac{S_\Omega-\pi r^2-r(C_\Omega-2\pi r)}{S_\Omega}-\frac{\pi r^2}{S_\Omega+rC_\Omega+\pi r^2}\times\frac{\pi r^2+r(C_\Omega-2\pi r)}{S_\Omega}\right) \quad \ldots(5)$$

Where, S_Ω is the monitored area; C_Ω is the perimeter of this area; and p is the initial coverage.

VF-PSO algorithm

As nodes are deployed randomly, the network coverage is low. In this article, a virtual force algorithm based on PSO (Particle Swarm Optimization) is proposed to improve the coverage quality of the monitored area. PSO is a population-based iterative evolution algorithm[23]. The combination of virtual force algorithm and PSO can improve the problem of insufficient optimization ability of virtual force algorithm and make particles effectively avoid falling into a locally optimal solution.

(1) Principle of VF-PSO algorithm

In the VF-PSO algorithm, the position of the sensor node is assumed to be the centroid of the node's sensing domain and the moving direction of the node is represented by the motion trajectory of the centroid. The centroid of this algorithm is regarded as a virtual charge and the monitored area as a virtual field. When the centroid moves, it is affected by the gravitational force and the repulsive force of the adjacent centroid. The resultant force of the two makes the centroid move towards a solution set that is conducive to maximizing the coverage of the area and finally makes the particles converge to the global optimal solution.

(2) Evolution and aggregation factors

Let the function value of the particle x_i after the k-th iteration be $f(x_i^k)$, the local optimal function value be $f(p_i^k)$, and the particle global optimal function value after the k-th iteration be $f(g^k)$. Before designing evolution factors and aggregation factors, the average of local optimums $aveP(pbest^k)$ of each particle after the k-th iteration is defined as[24]:

$$aveP\left(pbest^k\right) = \frac{\sum_{i=1}^{m} f(p_i^k)}{m} \quad \dots (6)$$

The average value of all particle function values $aveF(x^k)$ after the k-th iteration is:

$$aveF(x^k) = \frac{\sum_{i=1}^{m} f(x_i^k)}{m} \quad \dots (7)$$

Define the k-th iteration of the particle i as:

$$h1_i^k = \frac{f(p_i^{k-1})}{f(p_i^{k-1})} \quad \dots (8)$$

Define the k-th iteration of optimization degree of local average value as:

$$h2^k = \frac{aveP(pbest^{k-1})}{aveP(pbest^k)} \quad \dots (9)$$

The k-th iteration of the particle global optimization is defined as:

$$h3^k = \frac{f(g^{k-1})}{f(g^k)} \quad \dots (10)$$

The evolution factor equation that defines the k-th iteration is:

$$eva_i^k = a_1 h1_i^k + a_2 h2^k + a_3 h3^k \quad \dots (11)$$

Where, a_1, a_2 and a_3 are the correlation coefficients from 0 to 1, and $a_1 + a_2 + a_3 = 1$. Since the evolution factor is mainly based on the global optimal value-seeking degree, $a_3 > \max(a_1, a_2)$.

The aggregation factor equation that defines the k-th iteration is:

$$pol^k = \frac{aveF(x^k)}{aveP(pbest^k)} \quad \dots (12)$$

(3) Inertia weight

It can be known from Zhou *et al.*[24] and Lu *et al.*[25] that the size of the inertia weight has a great impact on the performance of the PSO. The inertia weight is improved by using equation (13):

$$w(t) = w_{max} - (w_{max} - w_{mim}) \tan\left(A_w\left(1 - \frac{t}{t_{max}}\right)^{\delta}\right) \quad \dots (13)$$

Where, t_{max} is the max number of iterations. w_{max} and w_{min} are maximum and minimum values of the inertia weight. δ is an adjustment element. A_w is acceleration coefficient. To prevent particles from flying out of solution space, the speed and position of particles need to be restricted.

$$v = \begin{cases} v_{max} & if\ v \geq v_{max} \\ v_{min} & if\ v \leq v_{min} \end{cases} \quad x = \begin{cases} x_{max} & if\ x \geq x_{max} \\ x_{min} & if\ x \leq x_{min} \end{cases} \quad \dots (14)$$

The particle position & velocity update equation is:

$$v_{in}^k = w(t)v_{in}^k + c_1 r_1\left(p_{bestin}^k - x_{in}^k\right) + c_2 r_2\left(g_{bestin}^k - x_{in}^k\right) + c_3 r_3 \theta_{vf} x_{in}^{k+1} = x_{in}^k + v_{in}^{k+1} \quad \dots (15)$$

Where, C_3 is the acceleration element. θ_{vf} is the changed angle of the particle by the action of virtual force, shown as equation (16). Other parameters are the same as the standard PSO.

$$\theta_{vf} = \theta_{max} \times e^{-\frac{1}{F_i}} \quad \dots (16)$$

Where, θ_{max} is the maximum angle of rotation. F_i is the virtual force resulting from the i-th node centroid.

(4) Particle force and energy analysis of VF-PSO

The moving particles are subjected to two virtual forces: gravitational force of the particles, and repulsive force of adjacent particles.

i) Gravity force on the particle

The gravity of the t-th uncovered point to the i-th centroid point can be calculated by equation (17).

$$F_{it} = \begin{cases} \frac{k}{(x_{ci} - x_t)^2 + (y_{ci} - y_t)^2} & if\ t \epsilon A_{\Omega}\ and\ t \notin A_y(i,r) \\ 0 & otherwise \end{cases} \quad \dots (17)$$

Where, (x_{ci}, y_{ci}) is the vertical and horizontal coordinate of centroid point C_i, (x_t, y_t) is the vertical and horizontal coordinate of *t*, A_Ω presents the monitored area, $A_y(i,r)$ presents the sensing domain of *i*-th node. The direction of F_{it} is from point i to point t.

ii) Repulsion of adjacent particles

To avoid the problem of coverage redundancy caused by the high density of nodes, this article assumes that there is a repulsive force between adjacent centroid points.

$$F_{ij} = \begin{cases} \frac{k'}{(x_{ci}-x_{cj})^2+(y_{ci}-y_{cj})^2} & if\ t \in A_y(i,r) \\ 0 & otherwise \end{cases} \quad \ldots (18)$$

Where, (x_{cj}, y_{cj}) is the vertical and horizontal coordinate of the centroid C_j, F_{ij} is the repulsive force of the centroid point C_i on the centroid point C_j, and the direction is from C_i to C_j. F_i is the vector sum of the gravitational force exerted by *m* nodes and repulsive force exerted by *n* adjacent nodes[11].

$$F_i = \begin{cases} \sum_{k=1}^{m} F_{ik} + \sum_{j=1, j\neq i}^{n} F_{ij} & m \geq 1, n \geq 1 \\ 0 & otherwise \end{cases} \quad \ldots (19)$$

The algorithm process flow of VF-PSO is presented in Table 1.

Table 1 — Dynamic deployment based on the VF-PSO algorithm

Step 1	The random deployment method is used to initialize the node deployment and give each particle in the particle swarm an initial speed and position. The position x_{id} of each particle is randomly generated in the range of $[-x_{\max}, x_{\max}]$, and the velocity v_{id} of each particle is randomly generated in the range of $[-v_{\max}, v_{\max}]$.
Step 2	Initialize the node energy and select a part of the redundant nodes to enter the dormant state.
Step 3	According to equation (1), the expected initial network coverage of the UWSN is given.
Step 4	At the beginning of VF-PSO, the number of nodes needed to reach the initial coverage was estimated according to equation (5).
Step 5	According to equation (15), the position, speed, and energy of the underwater sensor node are determined.
Step 6	It is determined whether the node energy in the working state is approaching the maximum node energy.
Step 7	Whether there is a coverage void-hole in the network. If so, adjust the node distance threshold D_{th}.
Step 8	The resultant force of each node is calculated.
Step 9	The local optimal solution and the global optimal solution are calculated and compared at the end of each iteration, and the global optimal solution is continuously updated.
Step 10	Speed and position of the sensor nodes are updated according to the resultant sum calculated in Step 8 and equation (19). Network coverage is also obtained.
Step 11	It is judged whether the coverage ratio and the global optimal solution or the number of iterations has reached a preset value. If not, it returns to Step 5 for loop iteration. If it is satisfied, the algorithm ends.

Table 2 — Simulation parameter

Monitored area (*km*^{2})	10*10
Sensing radius (*m*)	460
Initial coverage	0.75
Number of nodes	200
Maximum number of iterations	150
Node initial energy (*mAH*)	2500
Acoustic wave velocity (*m/s*)	1500
Transmission rate (*kbps*)	10
Frequency (*kHz*)	25

Simulation Results and Discussion

The simulation experiment of the proposed VF-PSO is performed on MATLAB, and simulation parameters are demonstrated in Table 2. The network coverage and energy cost of the proposed algorithm are compared with the PSO and Social PSO (SPSO) proposed by Zhou[24]. The network coverage layout before and after the simulation is shown in Figure 5. The result of effective coverage rate is presented in Figure 6. The network energy consumption result is presented in Figure 7. Compared with the algorithm by Du[26] for the average moving distance of nodes, the results are shown in Figures 8(a & b).

Figure 5(a) shows the initial network coverage of simulation, and Figure 5(b) is the network coverage after VF-PSO optimization. It is obvious that the nodes have been more evenly deployed and the network coverage ratio has been improved by VF-PSO.

Figure 6 shows the iteration curves of the three algorithms. The solid line is the iteration curve of the PSO algorithm, the asterisk line is the iteration curve of the SPSO algorithm, and the circle line is the iteration curve of the VF-PSO algorithm. It can be known from the simulation curve of Figure 6(a) that the number of iterations is the same. If the coverage algorithm uses the PSO algorithm, the algorithm

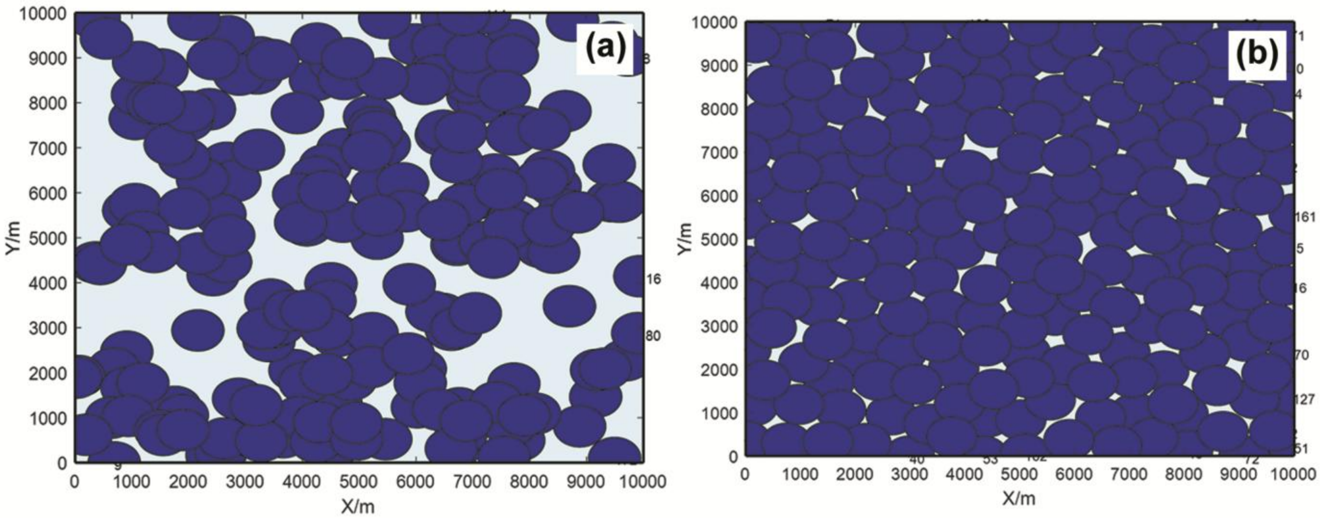

Fig. 5 — (a) Initial network coverage, and (b) Network coverage after VF-PSO optimization

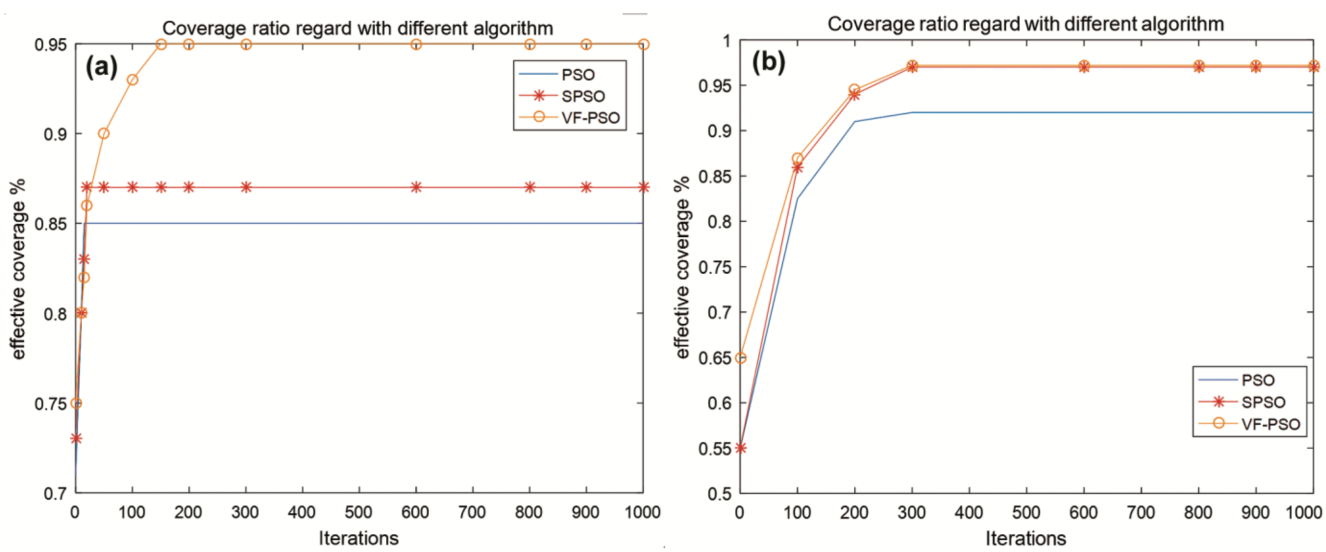

Fig. 6 — (a) Effective coverage ratio if nodes number is 200, and (b) Effective coverage ratio if nodes number is 300

converges to the local optimum prematurely, and the algorithm has reached convergence when the network coverage just reached 85 %. When using SPSO, it can be seen that compared with the former, its optimization effect is better and its coverage ratio reaches 87 % when the algorithm converges. However, it can be seen from the figure that the convergence rate is still too early and the coverage of the whole network is still low. As the number of iterations increased, the coverage eventually increased to 91 %. It can be seen from the comparative analysis that the sensor network using the VF-PSO algorithm has a significantly higher final coverage result than the sensor network using PSO and SPSO. However, the number of iterations required to achieve final convergence is significantly higher than the latter. In actual application, it is necessary to set a larger number of iterations for VF-PSO. From the simulation curve in Figure 6(b), it can be known that with the same number of iterations, the coverage of the VF-PSO, PSO, and SPSO is 97.2, 92 and 97 %, respectively. Since the number of nodes has increased, the overall coverage is greater than the coverage achieved by the 200 nodes in Figure 6(a).

It can be seen from Figure 7(a) that the energy consumption of the UWSN using PSO is higher than the other two algorithms during the simulation. The UWSN using SPSO has slightly higher initial network coverage than VF-PSO and the energy consumption per unit area is slightly lower than VF-PSO. However,

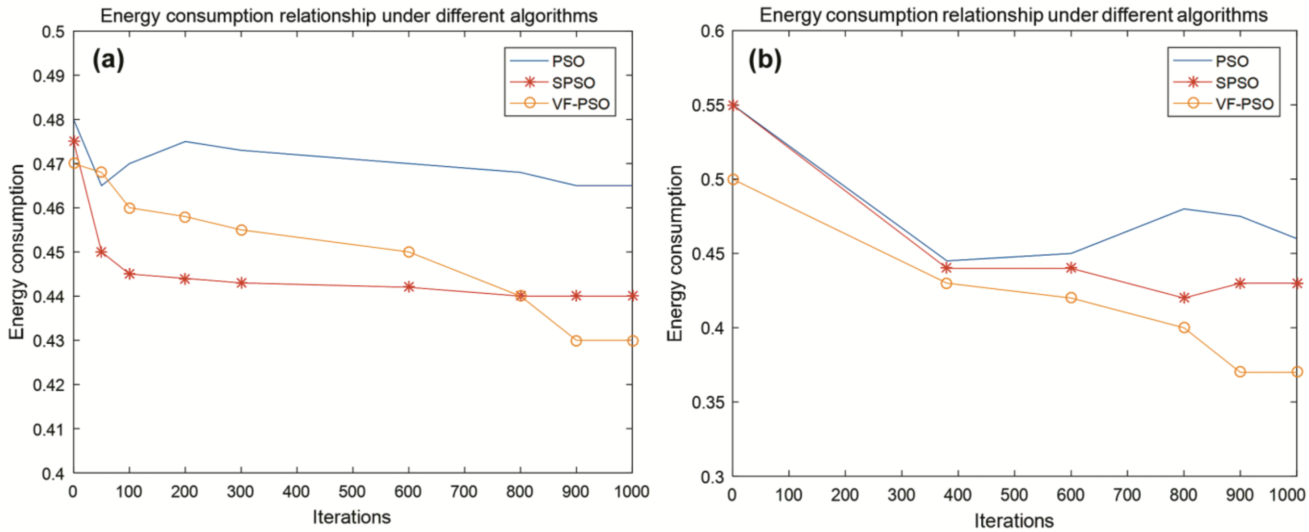

Fig. 7 — (a) Network energy consumption if nodes number is 200, and (b) Network energy consumption if nodes number is 300

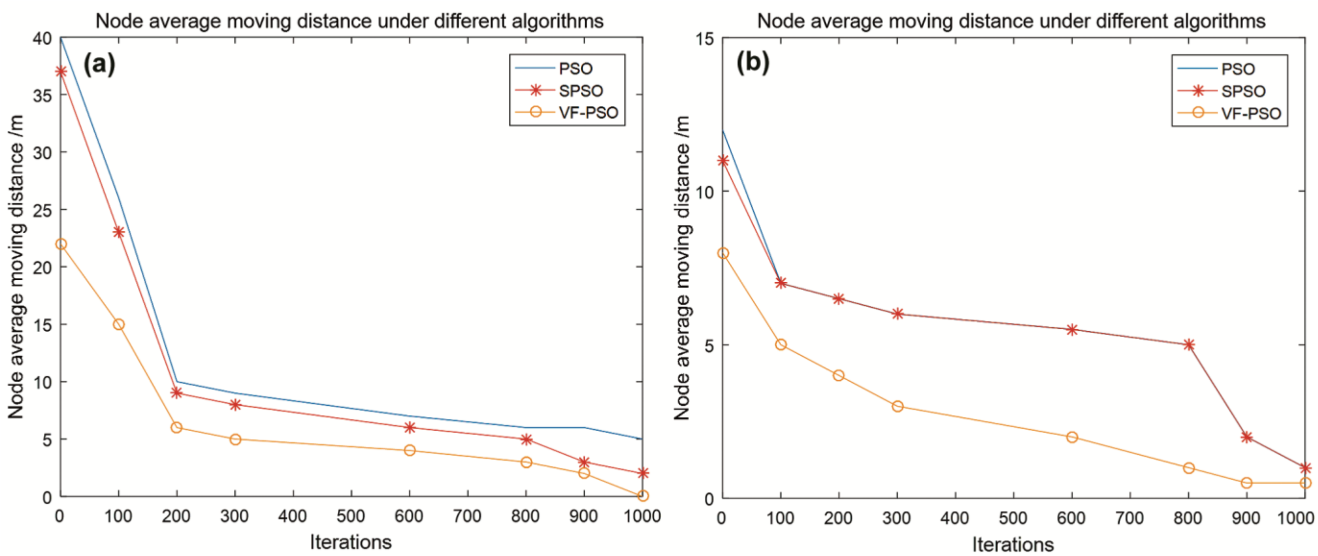

Fig. 8 — (a) Node average moving distance if nodes number is 200, and (b) Node average moving distance if nodes number is 300

compared with VF-PSO, the optimization degree of SPSO is still slightly worse. The UWSN using VF-PSO has relatively low network coverage at the initial stage and its energy consumption per unit area is slightly higher than SPSO. As the algorithm iterates, its network coverage gradually increases, the energy consumption per unit area gradually decreases and the subsequent remains stable. In Figure 7(b), due to the increase in nodes number, the overall energy consumption becomes larger, but with the increase in iterations number, the final energy consumption is still better than that in Figure 7(a).

From Figure 8(a), it can be seen that the average moving distance of PSO and SPSO with unadjusted perceptual radius is higher than VF-PSO with dynamically adjusted perceptual radius under the same number of iterations. After reaching the convergence of the algorithm, the coverage change is not great, but for PSO and SPSO with a fixed sensing radius, due to uneven distribution of the initial sensing nodes, the redundancy of the nodes will be relatively large and there will be many coverage holes. The VF-PSO algorithm will adjust the perception radius according to the changes in network coverage holes. As the number of iterations increases, the network nodes are more evenly distributed and the distances that the nodes need to move are getting shorter. The SPSO algorithm has poor optimization ability, and the PSO is prone to fall into a locally optimal solution. VF-PSO algorithm combines virtual force and PSO, which not only avoids the generation of a locally optimal solution but also accelerates the convergence speed of the algorithm. In Figure 8(b), as the number of nodes increases, the average moving distance of the overall nodes is lower than in Figure 8(a).

According to the simulation results, the VF-PSO could effectively improve the coverage ratio, reduce energy consumption and avoid the void-hole problem.

Conclusion

This article has studied the coverage optimization problem of UWSN and proposed the VF-PSO algorithm. The virtual force could guide the particle to the centroid of the node, accelerate the convergence of the particle to an optimal solution, and improve the effective coverage ratio of the network. The simulation results demonstrate the advantages of the algorithm in terms of convergence speed, energy consumption and coverage performance, thus avoiding the problem of network void-holes. In future research, we will focus on increasing the nodes number and proposing the algorithm to a marine ranching-based UWSN application, to verify its practical performance.

Acknowledgements

This work was supported by Shandong Provincial Natural Science Foundation under Grant ZR2020MF001, National Nature Science Foundation under Grant 61902205.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Ethical Statement

We certify that this manuscript is original and has not been published and will not be submitted elsewhere for publication while being considered by Indian Journal of Geo-Marine Sciences. And the study is not split up into several parts to increase the quantity of submissions and submitted to various journals or to one journal over time. No data has been fabricated or manipulated to support conclusions. No data, text, or theories by others are presented as if they were our own. The submission has been received explicitly from all co-authors. And authors whose names appear on the submission have contributed sufficiently to the scientific work and therefore share collective responsibility and accountability for the results.

Author Contributions

Paper writing, software and algorithm writing: YH. Formal analysis and draft writing: YS. Reviewing and editing: LC.

References

1 Yuan Y, Liang C, Kaneko M, Chen X & Hogrefe D, Topology control for energy-efficient localization in mobile underwater sensor networks using stackelberg game, *IEEE Trans Veh Technol*, 68 (2) (2019) 1487-1500. https://ieeexplore.ieee.org/document/8576653

2 Latif K, Javaid N, Ahmad A, Khan Z A, Alrajeh N, *et al.*, On energy hole and coverage hole avoidance in underwater wireless sensor networks, *IEEE Sens J*, 16 (11) (2016) 4431-4442. https://ieeexplore.ieee.org/document/7419228

3 Wang Z & Wang B, A novel node sinking algorithm for 3D coverage and connectivity in underwater sensor networks, *Ad Hoc Networks*, 56 (2017) 43-55. https://dl.acm.org/doi/10.1016/j.adhoc.2016.11.009

4 Sun Y, Hu Y, Chen L, Liu H, Chen J, *et al.*, The coverage optimization method for underwater sensor network based on VF-PSO algorithm, *2020 Chinese Control and Decision Conference* (CCDC), 2020, pp. 2008-2013. https://ieeexplore.ieee.org/document/9164708

5 Zou Y & Krishnendu C, Sensor deployment and target localization in distributed sensor networks, *ACM Trans Embed Comput Syst*, 3 (1) (2004) 61-91. https://dl.acm.org/doi/10.1145/972627.972631

6 Wang W, Huang H, He F, Xiao F, Jiang X, *et al.*, An enhanced virtual force algorithm for diverse *k*-coverage deployment of 3D underwater wireless sensor networks, *Sensors (Basel)*, 19 (16) (2019) p. 3496. https://www.mdpi.com/1424-8220/19/16/3496

7 Liu C F, Zhao Z, Qu W Y, Qiu T & Sangaiah A K, A distributed node deployment algorithm for underwater wireless sensor networks based on virtual forces, *J Syst Arch*, 97 (2019) 9-19. https://www.sciencedirect.com/science/article/pii/S1383762118305794

8 Elhoseny M, Tharwat A, Farouk A & Hassanien A E, K-coverage model based on genetic algorithm to extend WSN lifetime, *IEEE Sens Lett*, 1 (4) (2017) 1-4. https://ieeexplore.ieee.org/document/7973054/

9 Ghannadrezaii H & Bousquet J F, Maximizing network coverage in a multichannel short-range underwater acoustic sensor network, *Comput Netw*, 160 (2019) 1-10. https://www.sciencedirect.com/science/article/abs/pii/S1389128619306097

10 Li P, Wang S, Zhang H & Zhang E, Improved particle swarm optimization algorithm of clustering in underwater acoustic sensor networks, *OCEANS 2017 - Aberdeen*, (2017) 1-7. https://ieeexplore.ieee.org/document/8084869

11 Du C L, Shi W, Shi X, Chen X & Yu H, Study on virtual force-directed particle swarm coverage-enhancing algorithm for directional sensor networks, *App Res Comput*, 32 (8) (2015) 2450-2453.

12 Ma X & Kang J, A multi-detecting point based on virtual force-directed particle swarm optimization algorithm for coverage enhancement in directional sensor networks, *13th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, *Wuhan*, 2018, pp. 1195-1200. https://ieeexplore.ieee.org/document/8397891

13 Shi G X, *Node sleep scheduling simulation system and optimization algorithm*, (Tianjin University, China), 2012, pp. 19-24 (*In Chinese with English Abstract*). http://cdmd.cnki.com.cn/Article/CDMD-10056-1012022875.htm
14 Varma M K N, Kalyani M, Shin S Y & Park S H, Underwater spray and wait routing technique for mobile ad-hoc networks, *Indian J Geo-Mar Sci*, 48 (10) (2019) 1648-1655.
15 Mao Y F, Pang Y J, Li Y & Zeng W J, Using a velocity vector coordinate method for dynamic obstacle avoidance of autonomous underwater vehicles, *Har J Eng Univ*, 31 (2) (2010) 159-164. http://www.cnki.com.cn/Article/CJFDTotal-HEBG201002006.htm
16 Liu D L & Xu L J, Underwater robot controller design based on sensor networks, *Comput Measur Cont*, 23 (2) (2015) 439-442. http://www.cnki.com.cn/Article/CJFDTotal-JZCK201502033.htm
17 Jiang P, Ruan B & Tan K, Full-coverage required coverage-preserving algorithm for underwater sensor networks, *Chin J Sens Actuators*, 25 (11) (2012) 1591-1598. http://www.cnki.com.cn/Article/CJFDTotal-CGJS201211023.htm
18 Ge B, Liu W & Li H Z, Multi-agent itinerary planning based Voronoi dividing and Discrete multi-objective Particle swarm optimization, *International Conference on Internet of Things and Intelligent Applications (ITIA)*, 2020, pp. 1-5. http://ieeexplore.ieee.org/document/9312329/
19 Ammari M, Coverage in wireless sensor networks: a survey, *Network Protocols and Algorithms*, 2 (2) (2010) 27-53. http://connection.ebscohost.com/c/articles/63870871/coverage-wireless-sensor-networks-survey
20 Zhang H & Liu C, A review on node deployment of wireless sensor network, *IJCSI Intern J Comput Sci Issues*, 9 (6) (2012) 378-383. http://www.oalib.com/paper/ 2645098#. XnSFwrzE9bk
21 Yang H, Wang W Y & Tang Y, Node Scheduling algorithm based on communication and sensing coverage in WSNs, *Comput Sci*, 40 (7) (2013) 54-60. http://www.cnki.com.cn/Article/CJFDTotal-JSJA201307011.htm
22 Liu J, *Research on node deployment algorithm for underwater wireless sensor networks*, (Hangzhou Dianzi University, China), 2016, PP. 9-10 (*In Chinese with English Abstract*). http://cdmd.cnki.com.cn/Article/CDMD-10336-1016053616.htm
23 Wu Y L, He Q & Xu T W, Application of improved " adaptive particle swarm optimization Algorithm in WSN coverage optimization, *J Trans Technol*, 29 (4) (2016) 559-565. http://www.cnki.com.cn/Article/CJFDTotal-CGJS201604016.htm
24 Zhou J, Chen Y H, Liu G X & Xun W L, Summary of inertial weights in particle swarm optimization algorithm, *Guangdong Electric Power*, 26 (7) (2013) 6-12. http://www.cnki.com.cn/Article/CJFDTotal-GDDL201307004.htm
25 Lu L, *Research on wireless sensor network coverage based on particle swarm optimization algorithm*, (Lanzhou Jiaotong University, China), 2018, pp. 25-40 (*In Chinese with English Abstract*). http://cdmd.cnki.com.cn/Article/CDMD-10732-1018235724.htm
26 Du X Y, *Research on sensor network coverage algorithm for water environment monitoring*, (Nanjing University of Posts and Telecommunications, China), 2015, pp. 103-106 (*In Chinese with English Abstract*). http://cdmd.cnki.com.cn/Article/CDMD-10293-1016046367.htm