A Coverage and Connectivity of WSN in 3D Surface Using Sailfish Optimizer

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Abstract. Coverage and connectivity in the 3D surface of sensor nodes as the mountain is a critical problem in a wireless sensor network (WSN). This paper suggests a solution to multi-connectivity deployment WSN coverage based on combining Sailfish optimizer (SFO) with the characteristic of 3D surface topography. The target area divided into mesh grids of a size to establish the multi-connectivity of every grid. The cover set constructed through the direction gradient probabilistic model and connected graph and the joint points to graph within the grid by optimizing SFO. A large number of simulation experiments show that the proposed method can cover the target region and guarantee the connectivity and robustness of the network.

Keywords: Wireless sensor network; 3D surface; Multi-connectivity; Sailfish Optimizer

1 Introduction

The Wireless Sensor Network (WSN) is a self-organized multi-hop network composed of a vast number of sensor nodes distributed within the monitoring region[1]. The sensor node detects and gathers the information in the target area, and then it is transmitted to the sink node, which then transmits it across the Internet to the gateway node[2]. Therefore, the key to the research of WSN lies in the deployment of nodes and the communication of nodes. In the beginning, most of the research on WSN focused on a two-dimensional ideal plane, assuming that the sensing model of nodes is a disk sensing model[3]. In reference[4], a centralized approximation algorithm based on Voronoi partition is proposed. First, Voronoi partition the target area, then determine the redundant node dependency graph of the coverage set and then calculate the redundant nodes that can be closed at the same time through a greedy algorithm to get the final coverage. Finally, the algorithm of the minimum spanning tree is used to add auxiliary nodes to ensure the connectivity of the network. In reference[5], a grid-based distributed energy-efficient k-cover multi-connected deployment algorithm is proposed on the two-dimensional plane. The sensor nodes are randomly deployed in the target area. The nodes need to be dense enough to meet the requirements of k-coverage and multi-connectivity. The area divided into several grids. The length of the grid angle is the size of the communication radius to ensure that the nodes in a network can communicate with each other from each grid[6].

In order to solve the deterministic coverage problem in WSN, the three-dimensional surface is firstly reduced. Then the optimization algorithm is used to search for the global optimal coverage solution through continuous iteration. In the reference[7], for the 3D surface coverage problem, the target area is divided into n sub-areas. Then the multi-objective coverage problem is used to ensure the coverage and connectivity requirements of the network. Most of the researches on 3D surface problems is focused on coverage problems. Still, less on connectivity problems, often takes a long time to calculate and quickly leads to locally optimal solutions [8]. The observations of the previous works all are in two-dimensional or three-dimensional space at the problem of target coverage WSN. Several implementing metaheuristic approaches [9][10] are promising ways to solve the complicated issue of node coverage of WSN [11].

This paper explores the problem of target coverage of WSN on the 3D surface, suggests a target point distribution technique on the 3D surface to maximize coverage node location problems by applying a new metaheuristic algorithm called sailfish optimizer (SFO) algorithm[12]. In the process of the node perceiving the target points on the surface, there is the blind field of 3D perception, which realizes target coverage on the surface. The rest of the paper is organized as follows. Section 2 discusses the algorithm of the sailfish optimizer (FSO). Section 3 presents the mathematical coverage model. Section 4 gives the experimental results. Section 5 summarizes the conclusion.

2 Sailfish Optimizer (SFO)

Sailfish optimizer (SFO) is a new meta-heuristic developed by the inspiration of combining action behaviors of both types of fish sailfish and sardine. The mathematical model can be simulated by observing the action hunting attaching of the sailfish for the prey that is sardine [12][13]. The processing procedure of the SFO algorithm for optimization is presented as the following phases of processing descriptions.

Initialization: two vectors assigned for two types of fish: Sailfish and sardine: x_i^k and y_j^k(i ∈ {sailfishes}, j∈ {sardines}) are generated randomly, initializing positions with *Np* is the population size and k ∈{a number of iteration}; and in boundaries of the problem space with a feasible solution. We calculated the objective functions (or fitness function of the desired problem) for the sailfish and sardine, respectively. Elite sailfish (x_{eli}^k, eli ∈ $\{set\ of\ sailfish\}$) i.e.F(x_{eli}^k)≤ $F(x_i^k)$, $\forall k$. with the sardine (F (y_{iinj}^k), in j ∈ {a set of sardine}) i.e., (F (y_{iinj}^k)) ≤F (F (y_j^k), ∀ k. The fish positions work as agent searching in optimization is like the elitist procedure is to store elite sailfish and the injured sardine.

Locations updating:

Both sailfish and sardine are two types of location's fish can be improved the positions by updating their positions. The mathematical model equations of these updatings are stating as follows.

For sailfish position updating with the elite sailfish is toward a promising area in searching is given as follows.

$$x_i^{k+1} = x_{eli}^k - \lambda_k * (\beta * (x_{eli}^k + y_{inj}^k)/2) - x_i^k \qquad (1)$$

where x_i^{k+1} and x_i^k are generated as a new sailfish position over iteration of $(k+1)^{th}$, and i^{th} position the current sailfish, β is a random number ∈ [0,1], x_{eli}^k and y_{inj}^k are current elite sailfish and sardine positions; λ_k is a coefficient over iteration of k^{th}, which is calculated as follows.

$$\lambda_k = (2 * \beta * PD) - PD \qquad (2)$$

where, PD is indicated as the density of the school fish as prey. Alternation of attacks on the prey school, the sailfishes are hunting sardines; therefore, the victim number will decrease over iterations. PD is defined as follows.

$$PD = 1 - \frac{N_{sh}}{N_s + N_{sh}} \qquad (3)$$

where N_{sh} and N_s are the number of sailfish and sardines, respectively.

For sardine, position updating is considered as against the sailfish attacks. Let $y_j^{k+1}$and y_j^k be a sardine new and the current, and that its vector is updated locations as the following description.

$$y_j^{k+1} = r * (x_{eli}^k - y_j^k + AP) \qquad (4)$$

where r is a random number ∈ [0, 1]; the obtained best position so far x_{eli}^k is called elite sailfish; *Ap* is the attack power that is modeled as follows.

$$Ap = A * (1 - (2 * Itr * \varepsilon)) \qquad (5)$$

Factors decreased in power attack with A and ε are two variables; Itr is variable of iteration number. In the experiment, AP is set to 0.5 or less ($AP < 0.5$). A selected number α of sardines is defined as follows.

$$\alpha = \mathrm{N}s * AP \qquad (6)$$

where α is variable of selecting sardines that can be updated for is locations.

Whenever a sailfish i catches up a sardine j, it means the position of sailfish move to the location of the sardine. The hunted sardine is substituted by sailfish that is simulated as follows.

$$x_i^k = y_j^k \text{ if } (y_j^k) < F(x_i^k) \qquad (7)$$

where $x_i^k$and y_j^k indicate the position of sailfish *i* and sardine j at iteration k^{th} with condiction $(y_j^k) < (x_i^k)$. It is that the sardine population is decreased; it is going on to terminate with meet the termination condition or the end of processing optimization if reaching the target.

3 Mathematical coverage model

The coverage model for 3d space is a coverage model with node location as the middle and sensing distance as the radius. In the issue distribution in 3D space, node locations must be converted from a two-dimensional array $o(x, y)$ to a 3D array $o(x, y, z)$, which increases the height z coordinate. A complex homogeneous WSN as a sphere that is the basis for sensing and connectivity. $O_i(x_i, y_i, z_i)$ is taken as the sphere core for every sensor node Si (xi, yi, zi) in the network, and its sensing radius and contact radius are r and R, respectively, which are in the same system. Both nodes have the same range of feeling and contact. Simplifying the problem model is made with the following premises.

The sensor network is connected; that is, it is possible for all sensor nodes in the sensor network to receive information about their location and communicate. The location migration can be correctly realized by the sensor nodes, depending on the measurement performance. Regardless of the node's capability, the node is significant.

The probability of points ξ in the WSN is monitored by the sensor node S_i that denoted as $P(\xi, S_i)$; $d(\xi, S_i)$ is the distance between the target point and the sensor node; r is the sensing radius of the sensor node. The model is expressed as follows.

$$P(\xi, S_i)=\begin{cases} 0, & d(\xi, S_i) > r \\ 1, & d(\xi, S_i) \leq r \end{cases} \tag{8}$$

where $P(\xi, S_i)$ is the probability of points in the sensor node's sensing radius, and $d\ (\xi, S_i)$ is the distance between the points ξ, and S_i. The distance between points to Si can be calculated within the sensing range of the node.

$$d(\xi, S_i) = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (y_i - y_k)^2} \leq r \tag{9}$$

WSN often deployed with a large number of sensor nodes are randomly scattered in the three-dimensional space to be monitored.

Assumed that 3 points *A, B, C* are all within the sensing range of node Si that coordinates of the positions are $A(x_1, y_1, z_1)$, $B(x_2, y_2, z_2)$, and $C(x_3, y_3, z_3)$. The coordinates of *P(x,y,z)* can be expressed as follows.

$$\begin{cases} x = (x_1 + \lambda x_2)/(1 + \lambda) \\ y = (y_1 + \lambda y_2)/(1 + \lambda) \\ z = (z_1 + \lambda z_2)/(1 + \lambda) \end{cases} \tag{10}$$

where λ is variable of a fixed proportion point of the direct to line, three points *A, B,* and *C* can be monitored by sensor node *Si* on the 3D surface. The spatial position coordinates of sensor nodes Si and A, B, and C are known.

The formula for connectivity priority is as follows:

$$P_c = \frac{e_i^\alpha \cdot e_j^\alpha}{d(\xi_i, s_j)^\beta} + z \tag{11}$$

Among them, e_i and e_j represent the residual energy of nodes s_i and s_j; $d(\xi_i, s_j)^\beta$ is the Euclidean distance of nodes s_i and s_j; z is the parameter generated randomly to ensure that the value of P_C is not repeated as much as possible; α and β are the parameters set by the user and not 0.

The formula for override priority is as follows:

$$P_S = e_i^\lambda c^\theta + z \tag{12}$$

where: e_i represents the residual energy of node s_i; c represents the useful contribution of node s_i to the network; z is a randomly generated parameter to ensure that the P_s value is not repeated as much as possible; λ, θ are parameters set by the user and are not 0.

The target point set is divided into various meshes. Many meshes are calculated for pair of nodes that are activated according to the connectivity priority of a multi-connectivity graph and are established with its neighbor grid to ensure that there are at least two active nodes in each network.

The scale comparison of the active service area by the cell N nodes and the overall size of the restricted area. The field supervisory area formula is as follows:

$$P_{area} = \frac{\sum P_c - P_s}{m \times m \times h} \tag{13}$$

The SFO algorithm is used to optimize as minimum auxiliary nodes so that the nodes can communicate with each other. There are joint points in the connected graph formed by all awakened nodes. For each collective point, find out the double connected graph containing joint points, and find out a node other than the related node in each double connected graph to establish the double connected graph by adding auxiliary nodes. The majority steps of the processing of the proposed scheme procedure are expressed as follows.

Step 1: Initialization populations size of SFO N, set of target points St with connected graphs, Calculate fitness function Eq.(9).with the grid number q;

Step 2: Processing procedure of the coverage:

while(q)

For each mesh M_a, a multi-connected graph is built with its neighbor mesh;

q- -; The coverage probability is calculated of the mobile node to a pixel, according to Eq.(11).

$end\ while$

if （Grid M_a does not reach k-coverage）

According to the priority of coverage set, the node wakes up and enters the active state;

if (Mesh M_a is not connected)

According to the obtained optimal results, auxiliary nodes are added to make it connected;

Step 3: Join the optimized coverage mesh

if (Joint points in mesh M_a)

for Every joint a do

Let $B_1, B_2, \ldots, B_k$ be a bipartite graph with node a, let v_i be a node of B_i, and $V_i \neq a, 1 \leq i \leq k$

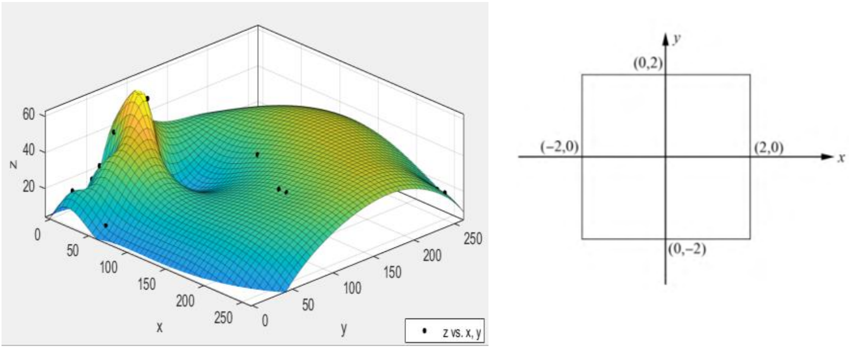
In the path of (v_i, v_{i+1}), $1 \leq i \leq k$, the least auxiliary nodes of communication are activated; The joint coverage is calculated according to Eq.(13).

Step 4: Terminal condition:

If condition of terminal meet e.g. max-iterations, threshold values

Repeat step 2 to step 4.

Step 5: Output the results

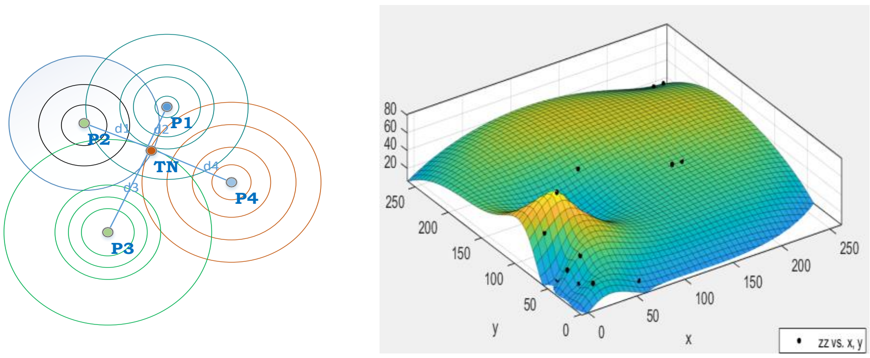


a) the 3D surface b) the projected two-dimension

Fig. 1. Projection of three-dimensional space surfaces to the two-dimension

4 Experimental Results

The majority steps of the processing of the proposed scheme procedure are expressed as follows. Assumed a deployed network with N mobile nodes that are placed arbitrarily in the desired area of $M \times M$ m2 and height H (M = 20, 30, 80, 130, 150, H = 2, 4, 5, 6). The sensing radius r of all mobile nodes is the same that is r set to 3 m of sensing radius, the communication radius is R set to 6 m; In probability model, λ = 0.9; α = 1.5; β = 1.1; The reliability measurement parameters is re = 0.5; r = 1.5 m; The maximum number of iterations $Tmax$ = 500; At the same time in simulating a series of experiments. Fig.1 shows the projection of three-dimensional space surfaces to the two-dimensional. It means the 3D surface is projected two-dimension.



a) several obstacle points b) settings the 3D surface

Fig. 2. The settings simulation environment and control parameters

The aim of this simulation test is to verify the efficiency of the proposed scheme that allows the node to leave these few obstacles and to begin tracking the corresponding target points in order to achieve the objective. Four obstacle points are chosen on the three-dimensional space surface and the location of the obstacle point projection on the plane such as: P1(1.5,1.5,0), P2(1.5,1.5,0), P3(-1.5,-1.5,1.0), P4(14.5,-15.5, 20.0), and P4(10.5,-1.5,30), respectively. The simulation environment and control parameter settings are the points that must be controlled on the floor, like *N* target points, but also four obstacle points. Fig. 2 displays the settings simulation environment and control parameters.

It is necessary to set the SFO algorithm parameters to get the ideal results fairly for the minimal number of sensor nodes is used to obtain maximum coverage of the target points on the three-dimensional terrain. Regardless of the inconsistency between the convergence speed and the precision of the SFO algorithm, the simulation check of the algorithm can be performed on the basis of the correct sacrificing of the convergence speed to get the most precise coverage. The SFO algorithm optimizes the positioning positions of sensor nodes in space so that the sensor nodes can know the maximum range of the target points on the space surface, to validate the method 's precision and viability. SFO-optimized distribution of sensor nodes in three-dimensional space where sensor nodes are spread uniformly in three-dimensional surface space example, the node coordinates are described as follows.

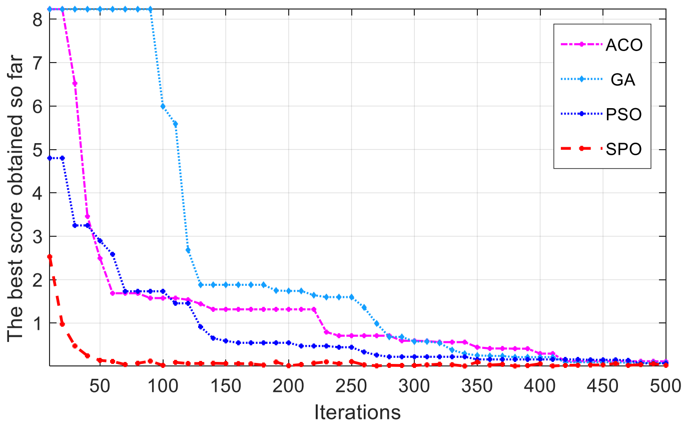


Fig. 3. Comparison of the proposed method (**SFO**) with the GA, PSO, and ACO for the objective function of coverage.

The obtained results of the proposed shame are compared with the other methods in the literature, e.g., Genetic algorithm (GA) [8]., Particle swarm optimization (PSO) [14], and Ant colony optimization (ACO) [15] for the coverage problem in WSN. Fig. 3 depicts the comparison of the proposed method with the GA, PSO, and ACO for the objective function of coverage and connective probability in WSN. It is clearly seen that the proposed scheme produces converge fastest in comparison.

Table 1. Comparisons of the results of the proposed scheme with the GA and PSO for different regions of the coverage optimization performance

Area	Mobile Nodes	**Proposed scheme (SFO)**		The PSO		The GA	
		Coverage rate	No. of Iterations	Coverage rate	No. of Iterations	Coverage rate	No. of Iterations
20 ×20×2	20	**81.8%**	187	77.3%	211	78.8%	423
30 ×30×4	50	**84.0%**	458	82.3%	420	80.1%	440
80 ×80×5	60	**81.0%**	468	80.2%	440	80.0%	450
130 ×130×6	160	**81.0%**	468	78.2%	446	77.0%	455
150 ×150×6	200	**81.0%**	468	80.2%	540	80.0%	456

Table 1 shows the comparisons of the results of the proposed scheme with the GA and PSO for different regions of the coverage optimization performance.

Observed Table 3, it is clearly seen that the proposed method can achieve the optimal global solution regardless of the different coverage areas. The proposed plan can cover the entire monitoring area with the best layout of the nodes.

5 Conclusion

In this paper, a new solution was introduced to node and connection coverage optimization in Wireless sensor networks (WSN) based on the Sailfish Optimizer (SFO). The architecture of the sensor nodes typically allowed optimal efficiency on the entire system life of the network based on node coverage and connection. The problem of node coverage in WSN is dedicated to the implementation of control and tracking applications. The desired deployment area of the network divided into mesh grids to establish multi-connectivity of every grid, the cover set constructed through the probabilistic model. The probability definition and geographic coverage rate are used to model as an empirical function of increasing node position to reach the optimal coverage. The SFO was applied to optimizing the connected graph of the multi-connectivity of a grid WSN and the joint points to a graph within the grid WSN. The node density cases were performed to determine the optimal method for maximum distribution trials in WSN. Experimental findings demonstrate that the proposed solution effectively increases convergence speed and node coverage efficiency, resulting in maximum network coverage impact and increasing network life.

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