Letter

A Coverage Optimization Algorithm for Underwater Acoustic Sensor Networks based on Dijkstra Method

Meiqin Tang, Jiawen Sheng, and Shaoyan Sun

Dear Editor,

This letter presents a coverage optimization algorithm for underwater acoustic sensor networks (UASN) based on Dijkstra method. Due to the particularity of underwater environment, the multipath effect and channel are easily disturbed, resulting in more node energy consumption. Once the energy is exhausted, the network transmission stability and network connectivity will be affected. Coverage optimization is a key problem in UASN, which directly affects the network lifetime. Considering the complexity of underwater acoustic channel, the energy transfer model is improved in this paper. Dijkstra algorithm is used to transform global optimization into inter node optimization to achieve optimal coverage. The feasibility and complexity of the algorithm are analyzed. Simulation results show that compared with similar algorithms, this algorithm can achieve better network coverage, which prolongs the network lifetime and improves the network performance effectively.

Underwater acoustics sensor networks deploy nodes with low energy consumption and limited communication distance in the designated water area, which use the self-organizing ability of nodes to collect data and sort out the information in the region [1], [2]. Different from land-based wireless sensor networks, the attenuation of high-frequency wireless waves by water medium is more obvious, and the noise of water environment has a great impact on communication. The narrow bandwidth, multipath transmission effect and high transmission delay of underwater channel reduce the communication efficiency of UASN. In underwater communication, sensor nodes are mainly powered by batteries, and it is difficult to supplement and replace energy. The battery energy of sensor nodes limits the network lifetime of UASN. Due to the high cost of underwater sensor nodes, improving the transmission reliability and ensuring the energy utilization of nodes often become the primary factor for the deployment of UASN nodes.

Since the underwater environment is complex and changeable, the research on underwater node deployment is directly related to the node energy, communication bandwidth and the accuracy of monitoring information of the network. Coverage refers to the effective monitoring range of UASN, which is an important indicator to measure the detection performance of UASN, and reflects the perception and monitoring ability of the network to the underwater environment. The larger the coverage area, the more data can be collected, which can save energy consumption and improve the service quality of the whole sensor network. However, the coverage process is not a static process, which is easily affected by the underwater environment and the underwater acoustic sensor itself. How to use as few nodes as possible to complete area monitoring and design coverage algorithm is a research hotspot in UASN.

The main contributions of this paper are summarized as follows. 1) The parameter is introduced to indicate whether the fixed sensor is activated. On this basis, a dynamic coverage model is adopted, which takes into account the real-time and complexity of the underwater acoustic channel. 2) Dijkstra is simple but powerful method for coverage optimization problem, which can ensure that the accessed node is the lowest cost node. The edge weight in Dijkstra optimization is used to determine the energy consumption in UASN. The proposed algorithm can quickly determine the position of the sensor in the target area, and fully consider the time and location constraints. 3) The proposed algorithm effectively optimizes the network coverage, which not only saves the energy consumption in the network, but also extends the network lifetime in UASN.

Related work: Information fusion builds the barrier coverage by enhancing the interaction ability of sensors to improve the detection probability. An energy efficient barrier coverage algorithm based on node coalition is proposed in [3] in underwater sensor networks. In [4], ant colony optimization (ACO) is used to minimize transmission loss and the propagation delay in underwater WSN environment. Brain storm optimization method and virtual force coverage optimization algorithm are proposed in [5], where the floating underwater nodes are driven to their relatively communicable positions, and the double mapping range and coordinate error of signal domain are established. An energy-efficient coverage optimization technique with the help of the Voronoi-Glowworm swarm optimization-K-means algorithm is proposed in [6], which considers optimum sensing radius calculation for efficient sensor deployment. The dimension of the solution vector of the coverage optimization algorithm changes with the size of UASN nodes. In addition, the actual underwater environment is extremely complex and unstable.

Compared with the above intelligent optimization methods, Dijkstra method [7] is more suitable for large-scale network optimization algorithm. It is widely used because of its simple concept, easy implementation and lax requirements for optimization functions. Dijkstra is applied to dynamic shortest path problem through retroactive priority queue in [8], where retroactive data structure gradually identifies the affected vertex sets, thus helping to adapt to changes in the minimum number of calculations. A method for spanning tree derivation based on the Prim-Dijkstra algorithm is proposed in [9], which enables the exploration of design space even in large-scale scenarios.

Problem statement: It is assumed that sensor nodes in UASN include two types: the base station node and the ordinary sensor node. The base station node is responsible for receiving the data information of the monitored sea area from the public sensor node; The ordinary sensor node is responsible for collecting the information in the covered sea area, and transmitting it to the receiver node in the form of multi hop transmission. For the actual underwater acoustic environment, the dynamic coverage of UASN when mobile sensors are moving is considered, represented by P_m. The probability is used to describe whether the target within the communication range is covered by the sensor.

$$P_m = 1 - \Pi_1^N [1 - x_i P_b],\ \ i = 1,2,\ldots,N \tag{1}$$

where P_b is the coverage of the binary sensor model [10], [11], N is the total number of sensor nodes. x_i is used to judge whether the fixed sensor is activated, which can be expressed by the following expression:

$$x_i = \begin{cases} 0, & \text{activated} \\ 1, & \text{otherwise.} \end{cases} \tag{2}$$

Energy consumption of sensor node when receiving data is defined as E_a, which can be obtained by

$$E_a = c_l E_e \tag{3}$$

where c_l is the bit length of data packet, E_e is the radio dissipation.

Since the transmission distance between two nodes determines the required energy, the energy consumption for transmitting data is

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defined as E_t, which can be calculated as

$$E_t = c_l E_e + c_l p_t t_t \beta(d,f) \tag{4}$$

where p_t is the received power level, t_t is the packet duration of single packet transmission, d is the transmission distance, $\beta(d,f)$ is the underwater attenuation from d (d is in km), which is calculated as follows:

$$\beta(d,f) = \left(\frac{d}{d_{re}}\right)^{\sigma} \alpha(f) \tag{5}$$

where d_{re} is the reference distance, σ is used to simulate the propagation geometry, which is the corresponding term of the path loss coefficient in the terrestrial radio. α is the absorption loss caused by the reduction of sound intensity, which is expressed by Thorp's formula [12], [13].

$$10\log\alpha(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75\times10^{-4}f^2 + 0.003. \tag{6}$$

Therefore, the total energy consumption of UASN can be expressed as follows:

$$E(x_i) = \sum_{i=1}^{N}(x_i E_a + x_i E_t). \tag{7}$$

Based on the above energy transmission model, the energy consumption between nodes in UASN can be calculated. Since the design of Dijkstra optimization algorithm needs to calculate the edge weight between nodes, and the purpose of this algorithm is to cover the target area with as few wireless sensor nodes as possible, the energy consumption can be used as the edge weight in Dijkstra optimization algorithm. The basic idea of Dijkstra algorithm is to select an edge with the smallest weight from each cut set of the graph, which forms the minimum tree. The graph in the proposed algorithm is composed of randomly distributed sensor nodes, and energy consumption between nodes corresponds to the weight in the minimum tree. The steps of the proposed UASN coverage optimization algorithm based on Dijkstra are as follows.

Step 1: Select the initial node, $u_j = \omega_{1j}$, $T = \emptyset$, $R = 1$, $S = 2,3,\ldots,N$, determine the randomly generated UASN nodes, and then calculate the weights from the initial sensor nodes to the other nodes respectively. The determined initial sensor nodes are taken as a set, and the remaining sensor nodes are taken as a set to be tested.

Step 2: Set $u_k = \min u_j = \omega_{ik}$, and $T = T\cup e_{ik}$, $R = R\cup k$, $S = \frac{S}{k}$. Since Dijkstra can ensure that the accessed node is the lowest cost node, the sensor node corresponding to the edge with the smallest weight is placed in the determined set, and the remaining sensor nodes are taken as the set to be tested. This can quickly determine the position of the sensor in the target area, thereby obtaining less energy consumption.

Step 3: If $S = \emptyset$, then stop iteration; Otherwise, $u_j = \min u_j$, ω_{jk}, $j\in S$, set $i = i+1$, and go to Step 2.

Feasibility analysis: Firstly, the randomly generated sensor nodes in the target area are divided into two parts, which are described by set S and set VS. For the convenience of description, the weights of edges in set S and set VS, that is, the values of energy consumption between nodes, are represented by set D and set D_t, respectively. And the weights of edges in set VS are regarded as variables to be tested, next three constraint definitions are given.

Definition 1: The path length of point n in S is recorded as $D[n]$, which constitutes the shortest path.

Definition 2: The variable to be tested conforms to

$$D[n] = \min D[m] + weight(m,n), \quad m\in S \tag{8}$$

Definition 3: If n is the smallest point in the variable to be tested of VS, then the corresponding $D_t[n]$ is the shortest path.

Since the algorithm starts with the initial sensor node, it can be proved $D[n] = 0$, which meets Definition 1, meanwhile the updated node can be proved to meet Definition 2. The proof by contradiction is adopted in Definition 3. Assuming that $D_t[n]$ is not the shortest path of n, since D_t is the shortest path constructed by the nodes in S, then the actual shortest path of n will pass through the node sets outside S, that is, the node set VS. Suppose the first point on the path not in the set S is l, so the expression of the actual shortest path is $m\to\cdots\to l\to\cdots\to n$. It has been assumed that the previous nodes belong to the set S, and according to Definition 2, the inequality can be obtained: $D_t[l] < D[n] < Dt[n]$. This is contrary to that n is the smallest point in the variable to be tested. Therefore, the hypothesis is wrong and Definition 3 is proved. The next step of the algorithm is to include n in the set S and update the distance variables to be tested in the set VS. It is found that the Definitions 1–3 are still valid. We conclude that the proposed Dijkstra optimization algorithm can construct the shortest path, that is, it can achieve the best coverage of the target area.

Complexity analysis: It is not difficult to see that the essence of the proposed Dijkstra optimization algorithm is that $n-1$ independent cut sets select an edge with the least weight in each cut set, which forms a minimum tree Therefore, we can further calculate the algorithm complexity. The first implementation of the second step is $n-2$ comparisons, the second implementation of the second step is $n-3$ comparisons, and so on, the total number of comparisons in the second step is $\frac{1}{2}(n-1)(n-2)$. In the implementation of the third step, the first is $n-2$ comparisons, and the second is $n-3$ comparisons. Therefrom the total number of comparisons is $(n-1)(n-2)$, correspondingly, the complexity of the proposed algorithm $O(n^2)$.

Numerical example: In this section, the proposed Dijkstra optimization algorithm is compared with the optimal coverage algorithms corresponding to ant colony optimization (ACO) [4], brain storm optimization (BSO) [5], glowworm swarm optimization (GSO) [6] using simulation, and the performance evaluation of the proposed algorithm is given. The simulation parameters are set as: a different number of sensor nodes are placed in a $300\ \mathrm{m}\times 300\ \mathrm{m}\times 300\ \mathrm{m}$ monitoring area with a transmission radius of 80 m; The reference distance d_{re} is set to 1 m, the counterpart of the path loss coefficient in terrestrial radio σ is 1.5; Transmitting power is 2 W.

1) Convergence comparison: Convergence is an important index to measure system performance in the underwater environment. Figs. 1 and 2 show the convergence of system coverage corresponding to ACO, BSO, GSO and the proposed Dijkstra algorithm under different node numbers, respectively. For intelligent methods, the population size is set to 30. It can be seen from Figs. 1 and 2 that the proposed algorithm is more effective than ACO, BSO and GSO. This algorithm can achieve better coverage convergence as soon as the number of nodes is 20 and 100. The reason is that Dijkstra algorithm is concise and easy to implement. The diversity of solution vectors has strong global search ability, which improves the robustness of the system. While the search ability of intelligent optimization algorithm in high dimensional optimization space is weaker than that in low dimensional space. Therefore, when optimizing large-scale sensor networks, ACO, BSO, GSO and other intelligent algorithms are more likely to fall into local extremum.

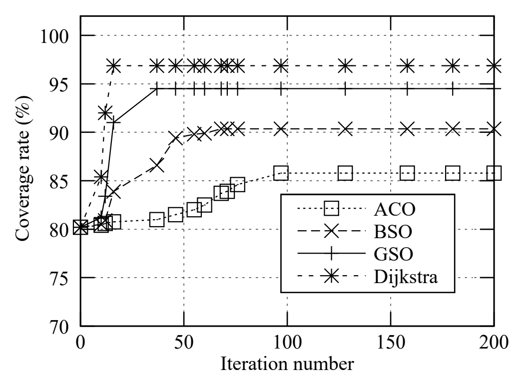

Fig. 1. System coverage when the number of nodes is 20.

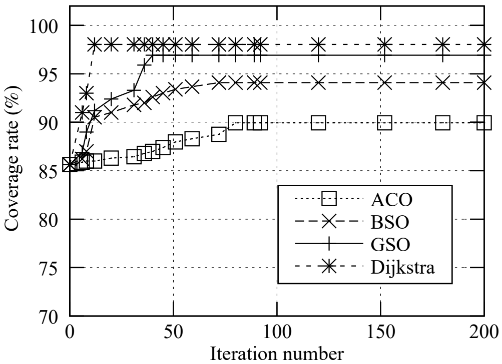

Fig. 2. System coverage when the number of nodes is 100.

2) Performance comparison: In order to further verify the effectiveness of the proposed algorithm, initial coverage, optimal coverage, convergence iterations and time consuming of the algorithms are compared, as shown in Table 1. The number of nodes corresponding to Cases 1 and 2 is 20 and 100, respectively. As seen from the table that the proposed algorithm and GSO have better coverage and shorter calculation time. Because GSO can compute multiple local optima of multimodal functions, whereas other swarm intelligent techniques can identify global optima. And in the proposed Dijkstra optimization algorithm, energy consumption is regarded as the weight of edges. By searching for the shortest path to optimize the coverage of the target area, the convergence speed and accuracy of the algorithm can be greatly improved.

Table 1. Performance Comparison of Different Algorithms

	Initial coverage (%)		Optimal coverage (%)		Iteration		Time (s)	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
ACO	80.21	85.62	85.78	89.95	97	80	31.9	24.72
BSO	80.21	85.62	90.37	94.1	68	62	25.67	22.6
GSO	80.21	85.62	94.5	96.92	37	33	19.94	16.45
Dijkstra	80.21	85.62	96.87	98.03	16	12	11.12	7.83

3) Influence of node number: By comparing and analyzing the convergence of different optimization algorithms, we can find that the coverage of the system is not only related to the number of iterations, but also affected by the number of nodes. Fig. 3 shows the coverage of different algorithms under different node numbers. It can be seen that the network coverage is proportional to the number of nodes. The more nodes are set, the higher the network coverage, but the network cost will be very high.

Conclusions: Aiming at the problem of low coverage in underwater acoustic sensor networks, a dynamic coverage model considering the actual characteristics of underwater acoustic channel is proposed. Then the Dijkstra method is applied to the proposed network coverage optimization problem. The method can determine the shortest path from the initial point to the arrival point by the smallest weight, so as to reduce energy consumption. The proposed Dijkstra algorithm in UASN can quickly determine the position of the sensors and solve time and place restriction. Experimental results show that this algorithm is more effective than other similar algorithms, which can not only save the energy consumption in the network, but also prolong the network lifetime. With the challenges in the complex underwater environment, there is great potential for future research in UASN. In terms of energy consumption, the specific node number setting and the distance between any two nodes are the contents to be further studied in the future.

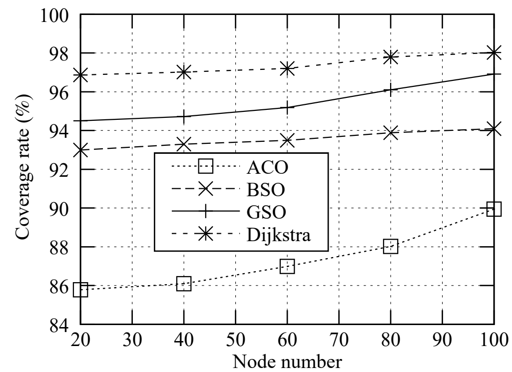

Fig. 3. System coverage under different node numbers.

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