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Node Selection Algorithm for Underwater Acoustic Sensor Network Based on Particle Swarm Optimization

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ABSTRACT Underwater target positioning technology is the most important part of UnderWater Acoustic Sensor Network(called UWASN), and it is one of the most important research directions in this field with broad application prospects in commercial and military fields. Due to the complex and variability of underwater acoustic environment, the underwater acoustic sensor network has the characteristics of fluidity, sparse deployment and energy limitation, which brings certain challenges to underwater positioning technology. Aiming at the scenario that the node redundancy in the underwater acoustic sensor network leads to low positioning efficiency, this paper considers the sound velocity correction factor based on the traditional anchor node selection algorithm in this paper. Under the premise of ensuring certain positioning accuracy, considering the communication overhead, node residual energy, position suspiciousness, sound ray propagation bending characteristics and other factors, the anchor node optimization mechanism which uses the particle swarm algorithm to iterate out the optimal sensor combination for improving the accuracy of positioning is designed. The simulation results show that the proposed algorithm shows small calculation, fast convergence and high positioning accuracy. It can effectively improve the energy utilization of nodes, balance positioning performance as well as energy use efficiency, and optimize the positioning result of UWASN, which is well suited for underwater acoustic positioning scenarios.

INDEX TERMS UWASN, node selection, sound velocity correction, underwater acoustic positioning.

I. INTRODUCTION

Marine engineering and related technologies play an increasingly important role in the human development process, especially in the submarine topographic exploration, marine engineering construction, marine resource development, and marine scientific research. The technologies of underwater operations and underwater positioning are extremely important in the construction of marine engineering, such as artificial island reef construction, submarine salvage, submarine pipeline laying, subsea tunnel development engineering, optical cable engineering and marine mineral resources exploration. At present, underwater positioning technology is widely used in offshore and deep sea engineering. However, underwater navigation systems, especially deep-sea positioning and navigation systems, are still relatively backward compared to the mature and widely used terrestrial satellite navigation and positioning systems. For the complex and variable deep sea environment, radio signals can only be transmitted over long distances through conductive brine at extremely low frequencies ($30Hz \sim 300Hz$) [1], [2], and only the wireless buoys near the sea can receive GPS positioning signals well. Therefore, the establishment of underwater wireless sensor networks for underwater positioning has become a common means for people to observe and predict the ocean and perform underwater navigation. The advent of underwater acoustic sensor networks (UWASNs) has enhanced marine environmental monitoring, auxiliary navigation, and marine military defense [3], which deploy a wide range of underwater instruments to form a large-scale

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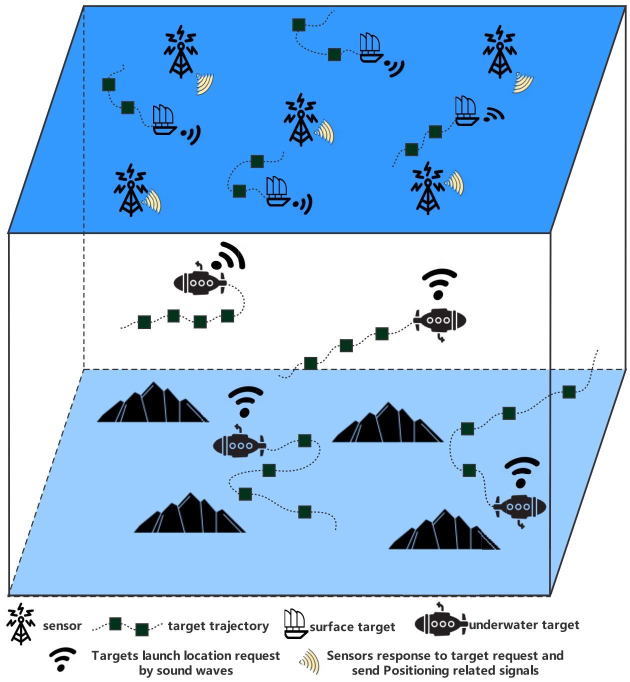


FIGURE 1. The positioning process of UWASN.

ocean data acquisition network for marine resource detection, data collection, and phenomenon monitoring. The UWASN mainly relies on sound waves for communication, which is generally composed of a certain number of wireless sensor nodes and an underwater three-dimensional network composed of communication links among these nodes. The nodes include wireless sensor nodes deployed in the seabed and the sea, and wireless buoy nodes updated by GPS timing on the sea surface. They send and receive information to each other within a certain coverage, perform cooperative tasks, communicate with terrestrial base stations, and meet the requirement of real-time applications combined with underwater acoustic channel characteristics.

The positioning process of the UWASN refers to the data collection scheme of [4], which is as shown as FIGURE 1. Firstly, the positioning device of the underwater target sends a positioning signal and then the sensor captures the positioning signal. Secondly, the sensor calculates the distance information by the time information obtained from positioning signal, and the poisitioning information and the self status information are composed into a sequence. Finally, the sequence is sent to the positioning device of the underwater target, and the positioning device selects the most suitable nodes according to the information of the sequence to solve the current position.

However, data collection schemes in UASNs are significantly different from those in wireless sensor networks due to high power consumption, severe propagation delay, and so on [5], which has a great influence on the positioning of the network. And the positioning accuracy has always been a serious problem. To solve this problem, the predecessors have done a lot of research, which can be basically divided into two categories.

The first category is considering the optimization method from the perspective of improving the capture accuracy of positioning signals based on a single sensor. Currently, most of the acoustic positioning methods designed for UWASN are distance-based. Under the premise that the velocity of sound waves can be estimated under water, ranging is essentially time measurement. For the process in which a single sensor captures a positioning signal, the task is to feedback the time information when the positioning signal is acquired. Therefore, the error is also reflected in the acquisition of these time information. It is mainly divided into two points. Firstly, since the underwater acoustic channel has the features of high delay, dynamic variation of delay, large attenuation, low communication channel bandwidth, serious multipath effect, and high transmission error rate, the positioning signal often tends to produce delay distortion, which may affect the accuracy of the time point when the sensor captures the positioning signal. Secondly, the traditional ranging methods obey the default that sound wave propagation delay is a fixed value (1500 m/s) which is multiplied by the measured time to obtain distance information. In fact, the water temperature, pressure, salinity and other factors of the underwater acoustic channel will cause the variation of sound velocity resulting in the bend of sound ray. Therefore, incorrect modeling of the sound velocity will also lead to large errors in ranging. In order to solve this kind of problem, we often consider the problem of signal detection and sound ray bending correction.

For the problem that the underwater acoustic channel distorts the delay of the signal in the process of capturing the positioning signal by a single sensor, the matching filter is used to generate the adaptive threshold and the method of using FRFT to improve the accuracy of the captured positioning signal has achieved good results in [6]. The traditional method of solving the problem of sound ray bending is based on indirect measurement. The indirect method is used to calculate the sound velocity of sea water, that is, the sound velocity is calculated by the sound velocity empirical model according to the depth, temperature and salinity [7]. In addition, some scholars also use many types of sound velocity models, including Dell Grosso, Leroy, Mackenzie and other 6 models which are introduced and compared in [7]. DNNs is applied for source localization in a shallow water environment and the results demonstrate that DNNs are effective for source localization in complex and varied water environments, especially when there is little precise environmental information [8]. However, the training and calculation of the DNN takes much time and does not meet the real-time application requirements of the underwater acoustic channel. Wu adopted an iterative method for sound ray correction of a long baseline Cartesian coordinates formation positioning system [9]. The method approximates the underwater sound velocity distribution to a vertical multi-layer gradient distribution, and iterates out a reasonable sound source position as well as the grazing angle of each angle. However, the fixed formula or model does not reflect the sound velocity transformation of all sea areas, so it is still necessary to use the measurement method. In [10], [11], the underwater sound velocity is divided into N structure regions. The horizontal distance of propagation of sound wave is calculated according to Snell's law, and the effective sound speedometer is established to correct the positioning error.

The second category is to consider and improve the factors that can affect the positioning accuracy when multiple sensors are co-located. In the process of selecting multiple sensors for co-location, the number of anchor nodes has a certain influence on the positioning accuracy. In theory, using more anchor nodes can improve the probability of accurate positioning, but sometimes adding anchor nodes is only increasing communication overhead and calculation amount, which may not be able to change the positioning performance. At the same time, due to the limitation of node energy, it is very important to select the appropriate number of nodes, improve the energy use efficiency, and reduce the unnecessary communication overhead as much as possible, thus prolonging the service life of the sensor network. Here are a few common influencing factors. Firstly, the sensor network node may move due to the action of the water flow and there is a positional uncertainty. However, in the mainstream positioning algorithm, the position of the anchor node must be known and determined. The uncertainty of self position will have a great impact on the algorithm, so the positioning process should give priority to nodes with smaller changes in position. Secondly, positioning process usually requires three to four nodes. If the arrangement of these nodes is not ideal (close to linear), the result of positioning will be greatly affected. Therefore, the positioning process should select the nodes with ideal arrangement. Finally, the nodes must have enough energy to complete the whole process including capturing the positioning signal and the communication transmission. Otherwise, the positioning process will become unreliable, that is, the positioning process should select nodes with more energy.

For the problem of node selection, the conventional method is to select some sensor nodes randomly. The network lifetime and the correlation of sensor nodes are not considered. Therefore, it is significant to adjust the sensor node selection scheme according to these factors for the superior performance. An optimized sensor node selection scheme is given based on Bayesian estimation theory in paper [12]. In [13], the error of the equilateral triangle positioning area is studied. Considering the distribution of location reference node, the equilateral triangle is designed as the basic positioning unit, which saves the computational overhead. Many land-based node selection algorithms only consider the factor of energy loss, but for the underwater acoustic positioning problem, the node selection algorithm also needs to consider the complexity of the underwater acoustic channel and the uncertainty of the node itself. In [14], the factors affecting underwater positioning accuracy such as node reliability, positional suspiciousness, and collinearity between nodes are analyzed. The energy distribution of the system is considered as well, and the Q-learning method is used to optimize the nodes and the system positioning mechanism.

Many existing methods only focus on the traditional evaluation indicators based on multi-sensors, but the interference factors that exist when a single sensor captures the positioning signal on the issue of multi-sensor co-location are not considered. For example, [14] only takes into account the influence factors of underwater location accuracy such as positional suspiciousness, collinearity between nodes, and node energy, but does not consider the problem of sound velocity correction. However, the final simulation results in this paper illustrate the necessity of sound velocity correction. In addition, most of the node selection methods are inefficient. Reference [14] solves the problem using the Q-learning method, but the efficiency is still relatively low. Because the Q-learning is highly complex and the calculation process is completed on the positioning device of the target. Therefore, the fast convergence of the algorithm also needs to be guaranteed.

Therefore, the focus of this paper is to propose an efficient scheme of multi-node selection and optimization of positioning accuracy. This method can not only contain the evaluation index of traditional multi-node selection, but also refer to the influencing factors of single sensor positioning error to a certain extent. The content of this paper is to quantify the sound ray bending as an index to measure the quality of the node. It is added to the several main influencing factors mentioned above to model the evaluation index, and propose the node selection algorithm combined with particle swarm optimization(called PSO). It utilizes the characteristics of fast convergence and high precision of PSO, so that the results can be quickly obtained, and the algorithm can be more adapted to the actual sensor. In addition, compared with the traditional evaluation index, the proposed algorithm adds several major error factors (position certainty, collinearity, energy loss) that affect the accuracy of underwater positioning when selecting multi-node co-localization. Furthermore, the factor of sound velocity correction is considered as well. It is proved by experiments that the addition of this factor has a significant improvement on the results. This paper mathematically models the purpose of positional certainty, energy, node collinearity, etc, and uses Snell's law to model the velocity of sound and uses the relationship between sound velocity and the time delay of the effective sound speedometer for the problem of sound velocity correction. Finally, the fitness function of the particle swarm optimization algorithm is designed according to all the above indicators, which optimizes the selection strategy of the anchoring node, saves the system energy consumption, and selects reliable nodes to obtain higher positioning accuracy and prolong the service life of the underwater acoustic sensor network. The algorithm framework is shown as FIGURE 2.

The chapters in this paper are organized as follows. Chapter II of this article describes some of the necessary methods for designing indicators. The purpose of

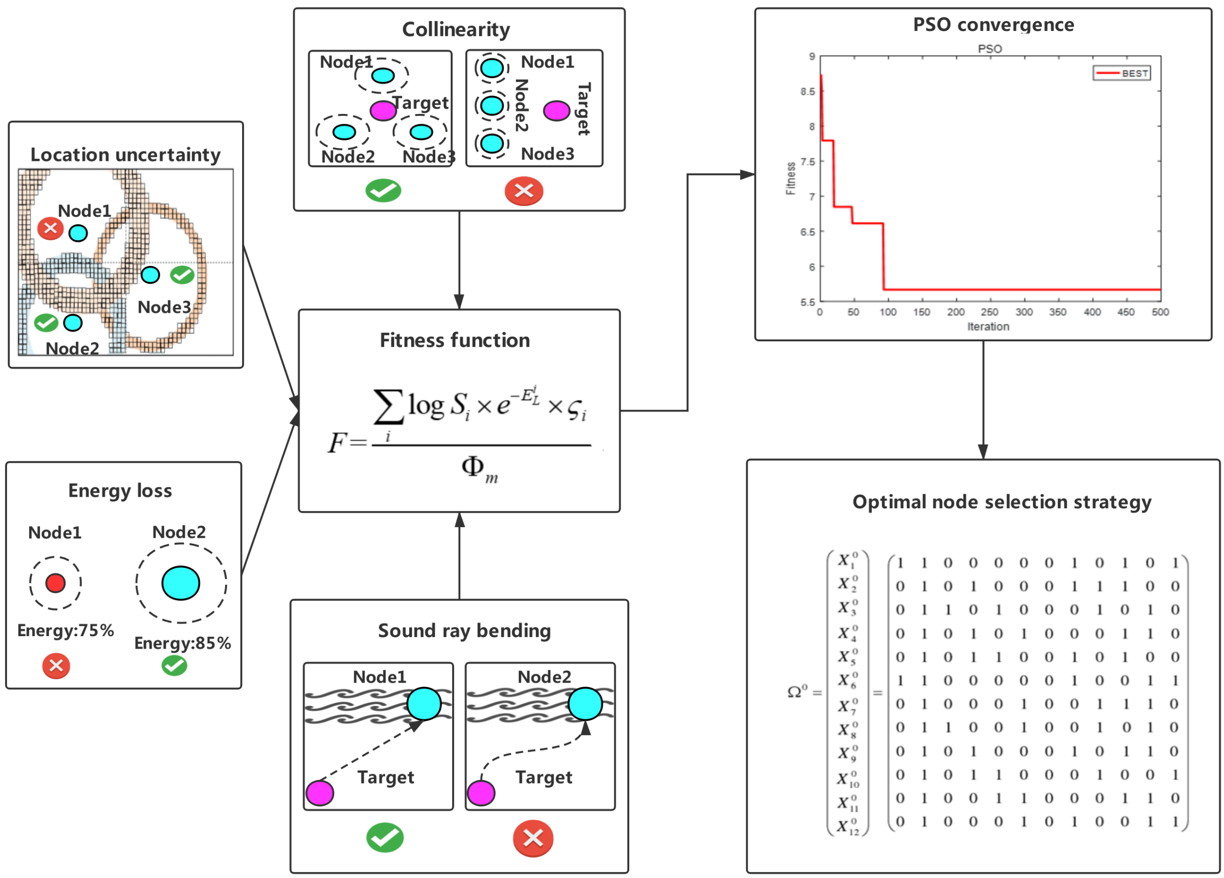


FIGURE 2. **The algorithm framework.**

chapter III is to obtain the fitness function of node selection and give the design indicators, including node position uncertainty, energy loss, collinearity as well as sound ray bending. And model them separately to obtain the indicator. Lastly, the various indicators are combined to obtain the fitness function. The chapter IV introduces the principle of particle swarm optimization algorithm, and combines the fitness function obtained in Chapter III to give an iterative algorithm. The chapter V shows the simulation of the proposed algorithm and the result analysis. Finally, compared with the traditional TOPSIS [15] algorithm from many different perspectives to prove the effectiveness of the proposed algorithm.

II. METHODOLOGY

In this chapter, the basic theory and methods used in sound velocity correction to pave the way for the sound velocity correction method in the chapter III will be introduced.

A. SNELL'S LAW AND SOUND VELOCITY CORRECTION

In the marine environment, in addition to physical properties such as temperature and salinity, an important factor which will seriously affect ocean sound velocity is the depth of seawater. Therefore, when characterizing sound rays, the vertical stratification characteristics of them are mainly considered, which is represented in FIGURE 3. Taking $h = 0$ as the sea level reference plane, if the sound velocity is assumed to be $c = c(h)$ distributed in the vertical direction and the sound source coordinate is $(0, h_0)$, the horizontal distance traveled by the sound ray at the signal receiving point (s, h) is:

$$s = \int ds = \int_{h_0}^{h} \frac{dh}{\tan \Theta(h)}, \tag{1}$$

In layered media, acoustic ray follows the Snell theorem

$$\frac{cos\Theta_0}{c_0} = \frac{cos\Theta_1}{c_1} = \frac{cos\Theta_2}{c_2} = \frac{cos\Theta_3}{c_3} = C, \tag{2}$$

where c_0 and Θ_0 are the sound velocity and the grazing angle at the sound source respectively. C is a constant. $\Theta(h)$ is the angle between the direction of sound ray and the horizontal direction at any depth, that is, the grazing angle, so the problem of seeking the sound trajectory is transformed into the problem of the direction $\Theta(h)$ of sound ray propagation at any depth.

From Snell's law we can derive

$$\tan \Theta = \sqrt{n^2(h) - \cos^2 \Theta_0}, \tag{3}$$

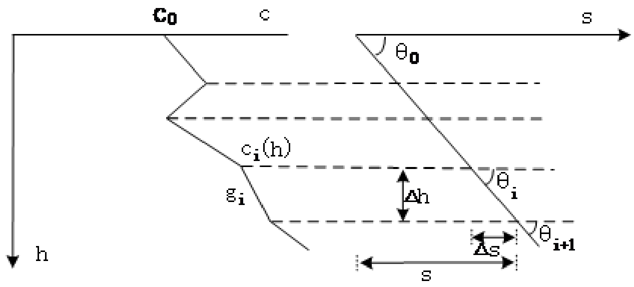


FIGURE 3. Sound ray diagram under vertical layering.

where, $n(h) = c(h_0)/c(h)$. h_0 is both the initial depth and the interval of sound velocity stratification. So the horizontal distance s is

$$s = \cos\Theta_0 \int_{h_0}^{h} \frac{dh}{\sqrt{n^2(h) - \cos^2\Theta_0}}, \tag{4}$$

For the vertical distribution of the sound rays, it is assumed that there are N constant sound velocity layers in the vertical direction, and each sound layer has a certain sound velocity gradient. When N tends to infinity, the sound velocity distribution map of each layer is characterized by the continuously changing sound ray distribution map.

Then the horizontal distance of the sound ray through the $i-th$ layer is ΔS_i, the vertical distance is Δh_i, and the sound velocity gradient of the $i-th$ layer is $g_i = \frac{dc_i}{dh}$. So the horizontal distance of each layer can be obtained according to the initial grazing angle Θ_0 of the sound ray and Snell's law, which is represented as:

$$\Delta s_i = \frac{h_i - h_{i+1}}{\tan[\frac{1}{2}(\Theta_i + \Theta_{i+1})]}, \tag{5}$$

The total horizontal distance s of the sound ray propagation is obtained by superimposing the horizontal distances of each layer:

$$s = \frac{c_0}{\cos\Theta_0} \sum_{i=0}^{N-1} \left| \frac{\sin\Theta_i - \sin\Theta_{i+1}}{g_i} \right|, \tag{6}$$

Then the actual straight ray distance L through which the acoustic signal passes is:

$$L = \sqrt{s^2 - \Delta h^2}, \tag{7}$$

B. EFFECTIVE SOUND SPEEDOMETER

Vincent (2002) theoretically deduced the velocity of sound and proposed the concept of effective velocity of sound between two points [16], [17]. The basic idea of the method is to establish a mapping relationship between the delay and the horizontal distance in the process of sound propagation, and establish an effective sound speedometer. When performing the positioning solution, the corresponding horizontal distance will be obtained through finding the effective sound speedometer by using the measured time delay value, which reduces the ranging error caused by the change of sound velocity in the positioning model. The method has a small amount of computation as well as high precision [10], and has great practical application value.

The effective speed of sound refers to the ratio of the linear distance of the acoustic signal between the anchor node and the object to be measured and the propagation time. By establishing an effective sound speedometer according to the measured environment of the ocean, the influence of the error caused by the bending of the sound ray can be eliminated, and the concept of effective sound velocity is introduced. In the process of positioning and ranging, the intermediate propagation process is ignored, and the corresponding actual linear distance is directly found according to the ratio relationship with lower the calculation complexity. The specific method is: determine the sound velocity profile according to the measured data of the ocean, vertically stratify the sound velocity, use Snell's law to calculate the grazing angle of each layer, and superimpose the horizontal distance to obtain the actual linear distance between the anchor node and the object to be tested. Therefore, in the case where the ocean sound velocity distribution is known, the effective sound speedometer of the sea area can be measured.

The sound ray correction method used in this paper establishes the correspondence between the actual propagation delay of the acoustic signal and the actual linear distance. During the positioning process, the effective sound velocity corresponding to the time delay can be found according to the delay in the signal propagation process, and the actual distance after the bending of the sound ray is obtained.

III. NODE SELECTION INDEXES DESIGN AND FITNESS FUNCTION ACQUISITION

The fitness function for node selection is given in this chapter. The fitness function is used to measure whether the node is suitable as the positioning node selected by the positioning device according to its size. The essence is to select the node with the least positioning error. Therefore, the design of the fitness function is closely related to the above various error factors. Next, the four factors mentioned previously (node position uncertainty, energy loss, collinearity, sound ray bending) will be analyzed and modelled mathematically to measure their metrics. Finally the fitness function will be given combine with the metrics.

A. POSITION UNCERTAINTY

The sea surface wireless buoy can be located by GPS satellite communication. And a large number of nodes below the sea surface are distinguished according to the roles and functions of different nodes in the sensor network, which can be divided into "master node" and "child node". The position accuracy of them also has certain differences. The "master node" directly communicates with the surface wireless buoy to obtain its location information, and the location of "child node" needs to be obtained by exchanging information with the "master node". The uncertainty of position is often expressed by "entropy". The position entropy H_i^S is used to describe the uncertainty of the position of the anchor node in the underwater acoustic sensor network. The greater the uncertainty, the larger the entropy. The entropy of the location distribution of the target positioning prediction is defined in [18]:

$$H_i^v = -\int p(z_i^v)\log p(z_i^v)dz_i^v, \tag{8}$$

Let i denote the $i-th$ anchor node, S_i denote the number of possible unit areas of the $i-th$ anchor node ($S_i \geq 1$), and P_i is the probability that the anchor node exists in the unit area of the region. Assume that the anchor nodes are evenly distributed within the area of the area, that is, the probability of being present in the unit area is equal. There is $P_i = \frac{1}{S_i}$, so the positional entropy is:

$$H_i^S = -\sum_1^{S_i} P_i \log_2 P_i = \sum_1^{S_i} \frac{1}{S_i}\log_2 S_i = \log_2 S_i, \tag{9}$$

And the nodes with smaller H_i^S tend to be selected.

B. ENERGY LOSS

In the positioning service of the underwater acoustic sensor network, energy is an important measure. It is necessary to consider whether the remaining energy of the anchor node can complete the positioning process of the unknown node, since the battery of the underwater node is not easy to replace. Once the energy of the node is exhausted, the underwater acoustic sensor network will lose the corresponding function and end its life. Therefore, the life of the network can be defined by the fact that the first node in the positioning process is exhausted and tends to be a "dead" state.

In the current simulation work, the residual energy of the sensor node is used as the preferred parameter index, and the residual energy is obtained by the difference between the initial energy and the transmission loss of each sensor node. Propagation loss refers to the fact that the energy of the acoustic signal exhibits a certain regular attenuation variation with the increase of the transmission distance. The total transmission loss (Transmitting Lost: TL) includes diffusion loss and absorption loss, which can be expressed by the following formula [19], [20]:

$$A(l,f) = l^k a(f)^l, \tag{10}$$

where k is the diffusion factor, and $k = 1.5$, f is the acoustic frequency, and the unit is kHz. l is the propagation distance, and $a(f)$ is the seawater absorption loss coefficient, which can be expressed as:

$$10\log a(f) = 0.002 + 0.11\frac{f^2}{1+f^2} + 0.011f^2, \tag{11}$$

The propagation loss TL is expressed in the form of dB as follows:

$$TL = 10\log A(l,f) = k \cdot 10\log l + l \cdot 10\log a(f), \tag{12}$$

Among them, the first item represents the expansion loss and the second represents the absorption loss. It can be seen from equation (12) that the propagation loss TL is not only related to the transmission distance, but also the frequency of the signal has a certain influence [20], [21].

Thus the residual energy E_L^i can be represented by equation (13), where $E_{L_0}^i$ is the initial energy of sensor node i:

$$E_L^i = E_{L_0}^i - TL, \tag{13}$$

And the nodes with larger E_L^i tend to be selected.

C. COLLINEARITY

In the UWASN, the positional relationship of different candidate nodes is an important index affecting the positioning performance. In [22], it is analyzed that multiple(≥ 3) reference nodes are on the same line, indicating that the position cannot be uniquely determined in this. So the collinear analysis of the selected sensor combination scheme is a necessary step in the positioning process. In the iterative process of the particle swarm algorithm, any three of the N sensor nodes selected are collinearly analyzed. Suppose nodes with coordinates (x_1, y_1) and (x_2, y_2) are selected as reference nodes, the linear equation is determined by them:

$$y = kx + b, \tag{14}$$

where k, b are the slope and intercept of the line, respectively. The collinearity ϕ_n is defined as the distance from the third node to the line:

$$\Delta = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}, \tag{15}$$

$$\phi_n = \frac{\left|y^i - kx^i - b\right|}{\sqrt{1+k^2}\cdot\Delta}, \tag{16}$$

where $\phi_n (n = 1, 2, \ldots n)$ is the collinearity of any three sensors in the selected sensor combination. The smaller the ϕ_n value is, the closer the three sensor nodes are to each other, and the higher the linearization degree is. Obviously, a larger ϕ_n is more suitable for the target and these eligible nodes will be selected as positioning nodes. The collinearity value of the particle takes the maximum value ϕ_m.

$$\phi_m = max\phi_n \quad (n = 1, 2\ldots N), \tag{17}$$

And the nodes with larger ϕ_m tend to be selected.

D. SOUND RAY BENDING

Since the underwater medium is non-uniform, the sound ray propagates along the spatial curve, and there is a difference in the velocity of sound at each point on the ray. Studies have shown that the sound velocity distribution has a relatively stable approximate vertical stratification, and it is known by radiology that the propagating sound rays in the underwater channel are curved in [23]. The bending of the sound ray means that the propagation delay of the acoustic signal from the transmitting point to the receiving point is greater than the straight line propagation and the influence degree of the bending of the sound ray at different positions in the space is distinct. The theoretical analysis of [24] shows that the longer the propagation time, the greater the difference between the effective sound velocity in various paths and the greater the positioning error caused by the sound velocity bending. Therefore, for each sensor node, if the sensor can estimate the sound velocity bending between itself as well as the target node and quantize it as an index for node selection, the accuracy of the positioning is inevitable to be improved.

The method of the effective sound speedometer described earlier will be used to obtain the effective sound velocity. First, we need to obtain the conditional information of the ocean sound velocity distribution and the corresponding distance, depth, and propagation delay. Next, the effective sound velocity is calculated and linked to the above conditional information via the speedometer. When we obtain a certain conditional information (such as the depth), we can find the corresponding effective sound velocity through the effective sound speedometer. The effective sound velocity can reflect the bending of the sound ray, so the sound ray bending factor is defined to measure it. The smaller the sound ray bending factor is, the smaller the sound line bending is, which can be measured by the difference between the effective sound velocity at the buoy and the target. The sound ray bending factor of $i-th$ node is defined as ζ_i that characterizes the bending degree is as follows:

$$\zeta_i = \frac{S_{en} - S_{e0}}{max\left[S_{en} - S_{e0}\right]}, \tag{18}$$

Since the depth information of the target to be tested can be obtained by the depth sensor installed thereon, the effective sound velocity value S_{e0} corresponding to the target can be obtained, and $S_{en}(n = 1, 2 \ldots, N)$ represents the effective sound velocity value of each sensor node. The nodes with smaller ζ_i tend to be selected.

The results of the sound speed correction will be mentioned in Chapter V.

E. FITNESS FUNCTION DESIGN

In the process of selecting the appropriate positioning objective function, there are two points to focus on. One is to ensure the positioning accuracy of the target node, and the other is to consider the energy efficiency of the whole system. For underwater acoustic positioning, the main influencing factors of positioning accuracy include the position uncertainty of the reference node and the ranging error of the reference node with the target node, and the collinearity among the nodes. The overall energy efficiency of the system is considered due to the long-term deployment of underwater acoustic sensors in the underwater environment and battery replacement is difficult. Coordinated positioning and transmission strategies can extend the service life of the positioning system.

The performance value of a single node is defined as C_i, and C_i needs to reflect the "health" of the node, which will affect whether the node tends to be selected. And we define that the smaller the C_i, the more "healthy" the node is. According to our previous analysis, H_i^S and ζ_i are positively correlated with C_i, and E_L^i is negatively related to C_i. Here the negative exponential function $e^{-E_L^i}$ is used to replace E_L^i, which is not only positively correlated with C_i and but also represent that energy is less affected when energy is more, and becomes larger when energy is less. Combined with the above analysis, C_i is defined as

$$C_i = \log S_i \times e^{-E_L^i} \times \zeta_i, \tag{19}$$

The performance value C_i considers the merits of a single node. In actual positioning, at least 3 reference nodes need to be used, so the objective function must be able to measure the quality of multiple reference node combinations. The significance of the objective function is that it can make the strategy iterate to the low uncertainty and high energy node direction, and select a node selection scheme with better topology. The weights of these reference nodes should be consistent, so they are superimposed into the objective function in the form of cumulative performance values. And it can be seen from the previous analysis that the collinearity is negatively correlated with F, and the combination cannot be selected when the collinearity is zero. Therefore, we define the objective function F as

$$F = \frac{\sum_i \log S_i \times e^{-E_L^i} \times \zeta_i}{\Phi_m}, \tag{20}$$

The objective function F here will be used as the fitness function F_i in the PSO algorithm of the next chapter. The role of F_i is to judge the quality of the $i-th$ combination. Obviously, the smaller the fitness function F_i, the more appropriate the combination, so that we can convert the node selection problem into a solution to the minimum value of the fitness function.

IV. NODE SELECTION ALGORITHM BASED ON PARTICLE SWARM OPTIMIZATION

In the last chapter, we obtained the fitness function of the node selection. The next step is to find a node selection combination that allows the fitness function to approximate the optimal solution. The binary particle filtering algorithm is used in the solution process. The association between the algorithm and the fitness function will be introduced. And the application in node selection as well as the corresponding algorithm will be given.

A. BINARY PARTICLE SWARM OPTIMIZATION

Particle swarm optimization(PSO) originated from the simulation of biological behavior in nature, that is, the simulation of the social behavior of an individual in nature. In the PSO, each particle represents a potential solution in solution space. Each particle has two properties(the velocity V and the position X). The velocity represents the speed at which the particle changes to a space vector, and the position represents the space vector where the particle is currently located. The goal of particles is to approach as close as possible to the optimal solution of the current solution space, and the criterion evaluating the state of these particles is the fitness function.

In the particle swarm algorithm, each particle starts from a random location and iteratively searches the optimal solution within the defined range.In each round of calculation, each particle moves according to its current calculated speed, starts from the current position, and calculates its fitness p_i through the fitness function.In this way, the system can evaluate the best particles in the current round and the best particles p_g in the global. At the same time, other particles adjust the velocity according to the speed update formula based on the difference between their own fitness p_i and the global optimal particle p_g, so that approach the optimal particle in the next iteration.

Eq(21) and Eq(22) represent the particle velocity update formula and position update formula:

$$v_{id}^{k+1} = v_{id}^{k} + c_1 r_1 (p_{id} - x_{id}^{k}) + c_2 r_2 (p_{gd} - x_{id}^{k}), \quad (21)$$
$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}, \quad (22)$$

where $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, representing the position vector of the $i - th$ particle in D-dimensional solution space. $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ represents the moving speed of the $i - th$ particle. x_{id} represents the $d - th$ component of x_i. k is the current iteration round. r_1 and r_2 are random numbers between [0, 1] to achieve group diversity. c_1 is a learning factor that represents the degree of individual optimal learning of the particles. c_2 is the acceleration factor, which represents the degree of global optimal learning of the particles. The PSO makes the particles have the ability of self-learning and self-summary through these two parameters, which respectively represent the learning intensity from the particle to its historical optimality and the global optimal of the system. In this way, the particles can be completely converged by continuously iterating. Appropriate adjustment of the values range of these two parameters can reduce the probability that the algorithm converges to the local optimum and accelerate the convergence speed of the PSO.

The traditional PSO is mainly applied to the optimization of continuous solution space, and it is difficult to solve the optimization problem of discrete solution space. Therefore, PSO has developed a binary particle swarm optimization algorithm (called BPSO) for discrete solution space optimization [25]. In the BPSO, the position of each dimension in the solution space is limited to 0 or 1, and the velocity is converted into a probability function, that is, the probability that one dimension of the solution space takes 0 or 1. The mapping of speed is generally implemented by the sigmoid function:

$$s(v_{id}) = \frac{1}{1 + e^{-v_{id}}}, \quad (23)$$

where s represents the probability that the particle takes 1 at position x_{id}, and the position of the particle changes according to

$$x_{id} = \begin{cases} 1 & \mathit{if}\ \mathit{rand}() \le s(v_{id}) \\ 0 & \mathit{otherwise} \end{cases}, \quad (24)$$

where $rand()$ is a random number evenly distributed between [0, 1]. In addition, in order to avoid the particle speed v_{id} being too close to 0 or 1, v_{id} is usually limited to a range.

B. DESIGN OF NODE SELECTION ALGORITHM BASED ON BPSO

In the process of using the PSO for node selection, we need to consider how to represent the corresponding data. In the node selection problem of UWASN, each particle has N binary elements, and N is the numbers of sensors determined by the current system. Each binary element of the particle represents the state of a hydroacoustic sensor node. The value 0 means that the current sensor node is not selected by the positioning system in a dormant state, while the value 1 represents that the current sensor node is selected to calculate the position information. Combined with the fitness function mentioned in Chapter III, the steps of the node selection algorithm based on BPSO can be described as

Algorithm 1 Node Selection Algorithm Based on BPSO

Input: Stop criteria(Number of iterations or maximum allowable error) and positioning information
Output: Global optimal solution of particles(Particle selection strategy)
Begin:

Randomly initialize the $x_i = (x_{i1}, x_{i1}, \ldots, x_{iD})$ and $v_i = (v_{i1}, v_{i1}, \ldots, v_{iD})$.
while not meet the requirement of stop criteria **do**
  for each particle **do**
    Calculate the fitness value F_i according to Eq(20);
    // Update individual best fitness
    if $F_i < F_{ib}$ **then**
      $F_{ib} \Leftarrow F_i$;
      $P_i \Leftarrow x_i$;
    end if
    // Update group best fitness
    if $F_{ib} < F_{gd}$ **then**
      $F_{gb} \Leftarrow F_{ib}$;
      $P_g \Leftarrow P_i$;
    end if
  end for
  for each particle **do**
    Calculate the velocity v_i according to Eq(21);
    Calculate the position x_i according to Eq(22);
  end for
end while

Where v_i represents the moving speed of $i - th$ particle, x_i represents the position vector of $i - th$ particle, P_i represents he best position of $i - th$ particle history, F_{ib} represents the best fitness of $i - th$ particle history, P_g represents the best position of particle group history and F_{gb} represents the best fitness of particle group history.

Next, we analyze the reason why the PSO algorithm can efficiently calculate the optimal solution. Specifically, each particle represents a choice of nodes selection, which is an

n-dimensional binary vector(n represents the number of candidate node). A value of 1 in the vector means that the node is selected, and a value of 0 means not. We can calculate the fitness F_i of this particle by combining the fitness function of Eq(20) with several parameters (S_i, E_L^i, etc.) obtained by the selected nodes in the vector. During the iterative process, the particle always acquires the particle state P_g (vector) corresponding to the global optimal solution of all particles and the particle state P_i (vector) corresponding to the historical optimal solution of the particle till now. Therefore, $p_{id} - x_{id}$ gives the direction in which the particle is approached to the P_i and $p_{gd} - x_{id}$ gives the direction in which the particle is approached to the P_g. In addition, $c1$ and $c2$ indicate that one direction is preferred. $r1$ and $r2$ bring randomness, which let particles search for a larger range. After each iteration, this particle is roughly approaching in the "optimal" direction(optimal direction under known conditions). With large number of particles and Large search range, the best or a better solution is quickly found. The next chapter will verify the efficiency of the PSO algorithm through simulation experiments.

V. SIMULATION RESULTS AND DISCUSSION

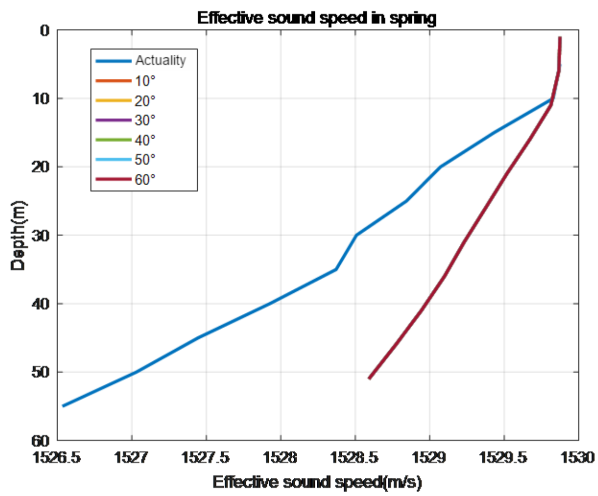
This chapter first introduces the establishment of the effective sound velocity meter and its simulation results, and then compares the simulation experiments with the commonly used TOPSIS algorithm to verify the efficiency and reliability of the proposed algorithm. Finally, the complexity and convergence analysis are given to prove the scientific results of the simulation.

A. ESTABLISHMENT OF EFFECTIVE SOUND SPEEDOMETER

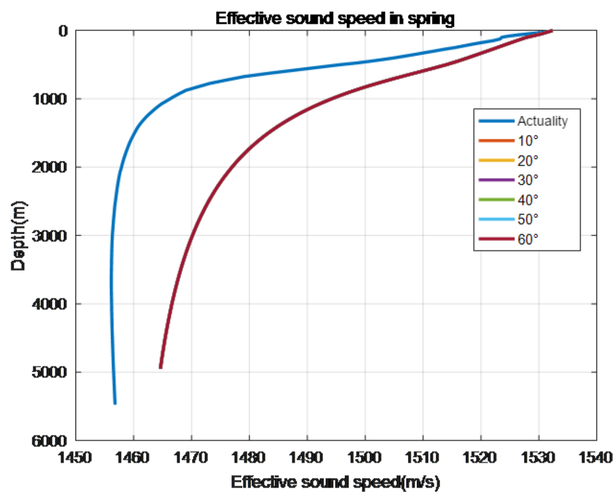
According to the sound ray bending correction algorithm described above, this paper separately uses the deep sea($24.5°W, 128°E$) and shallow sea($24.5°W, 119.5°E$) measured sound velocity data published by NODC to explore the relationship between sound ray bending and depth, glancing angle and propagation time. We will further discuss the relationship among these variables by comparing the simulation results of shallow sea scenes and deep sea scenes.

1) RELATIONSHIP BETWEEN EFFECTIVE SOUND VELOCITY AND DEPTH

FIGURE 4 a and 4 b represent the change trend of the effective sound velocity with ocean depth in deep sea and shallow sea environments, respectively. The blue curve in the figure represents the actual sound velocity data, and the curves of different colors represent the effective sound velocity maps made at different incident angles. It can be seen from the figure that the effective sound velocity curves of different incident angles are completely coincident in the deep sea or the shallow sea environment. That is, at a certain depth, the effective sound velocity of the ocean is independent with the initial glancing angle of the sound ray. In addition, the effective sound velocity curve has the same overall trend



(a) Shallow sea scenes.



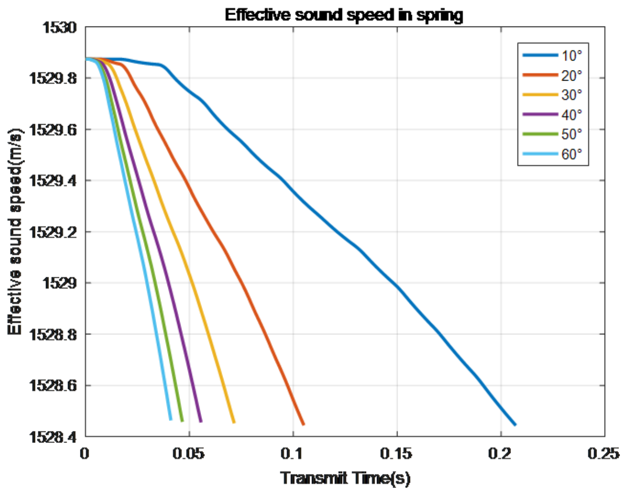
(b) Deep sea scenes.

FIGURE 4. Relationship between effective sound velocity and depth.

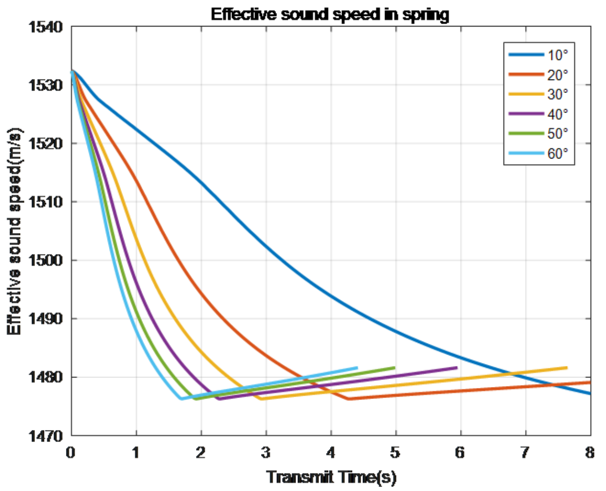
with the sound velocity profile curve, and the curve is relatively flat because it is the ratio of the cumulative variation of the stratification distance to the propagation delay.

2) RELATIONSHIP BETWEEN EFFECTIVE SOUND VELOCITY AND PROPAGATION DELAY

FIGURE 5 describes the relationship between effective sound velocity and acoustic signal propagation delay in deep sea and shallow sea environments, respectively. In this way, during the underwater acoustic positioning, the effective sound velocity value can be directly obtained by the currently measured acoustic signal propagation time and the glancing angle. Thereby the actual propagation distance of the anchor node can be obtained by the the effective sound velocity and propagation time which improves the accuracy and efficiency of positioning. Specifically, in the process of underwater acoustic positioning, the time delay of the signal transmitted between the anchor node and the object can be derived from

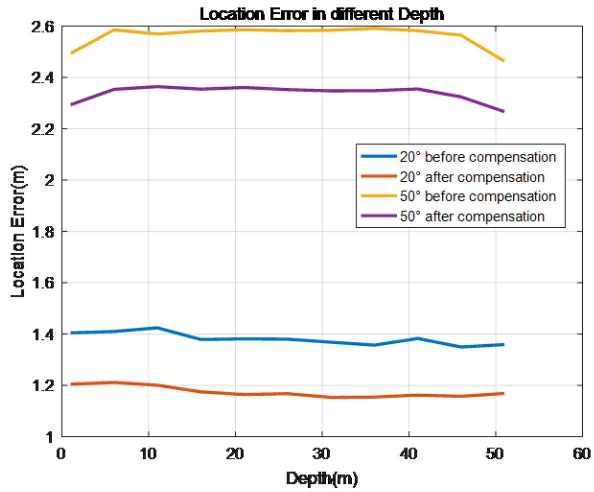


(a) Shallow sea scenes.

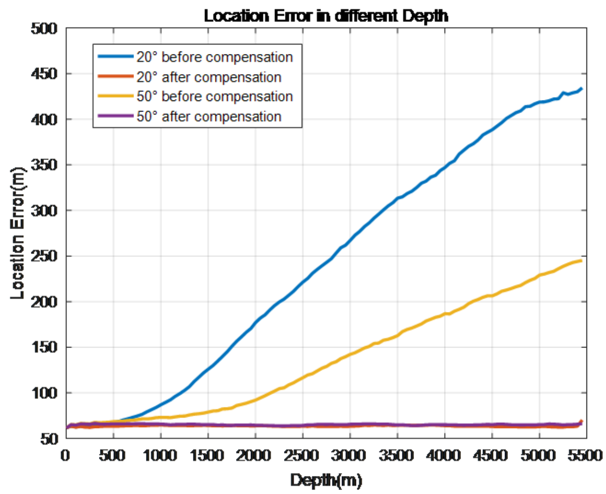


(b) Deep sea scenes.

FIGURE 5. **Relationship between effective sound velocity and propagation time.**



(a) Shallow sea scenes.



(b) Deep sea scenes.

FIGURE 6. **Results of using effective sound speedometer.**

the time when the synchronization signal is captured. And then according to the known initial glancing angle, and the corresponding effective sound velocity can be obtained. The rectangular area enclosed by this point with the coordinate axis is the actual distance between the two points, so the ranging error is corrected.

3) RESULTS OF EFFECTIVE SOUND SPEEDOMETER

FIGURE 6 b is a comparison of the positioning error before and after the correction of the sound ray bending in the deep sea environment. In the deep sea environment. The positioning error of deep sea mainly comes from two aspects. One is the sound velocity drift caused by the vertical variation of sound velocity, and the other is the channel noise error of the ocean channel itself. It can be seen from the simulation diagram that for different emission angles, sound velocity correction can well eliminate velocity drift caused by the sea depth, and achieve better positioning correction. The main reason is that under deep sea conditions, the sound velocity changes more severely than the shallow sea environment. Direct use of uncorrected sound velocity values will lead to large ranging errors, resulting in offsets in positioning and large positioning errors. After the sound velocity is corrected, relatively accurate ranging information can be obtained for better positioning. According to the refraction theorem, the lower pitch angle also brings more positioning errors, but after correction, the error caused by the small pitch angle can be better eliminated.

FIGURE 6 a is the positioning errors before and after the correction of the sound ray bending in the shallow sea environment. It can be seen that the sound velocity correction can repair the ranging error in the positioning to a certain extent, thereby correcting the actual positioning error. However, due to the shallow sea environment, the problem of sound velocity drift caused by change of sea depth is not obvious. However, the error between the anchor node and the target distance

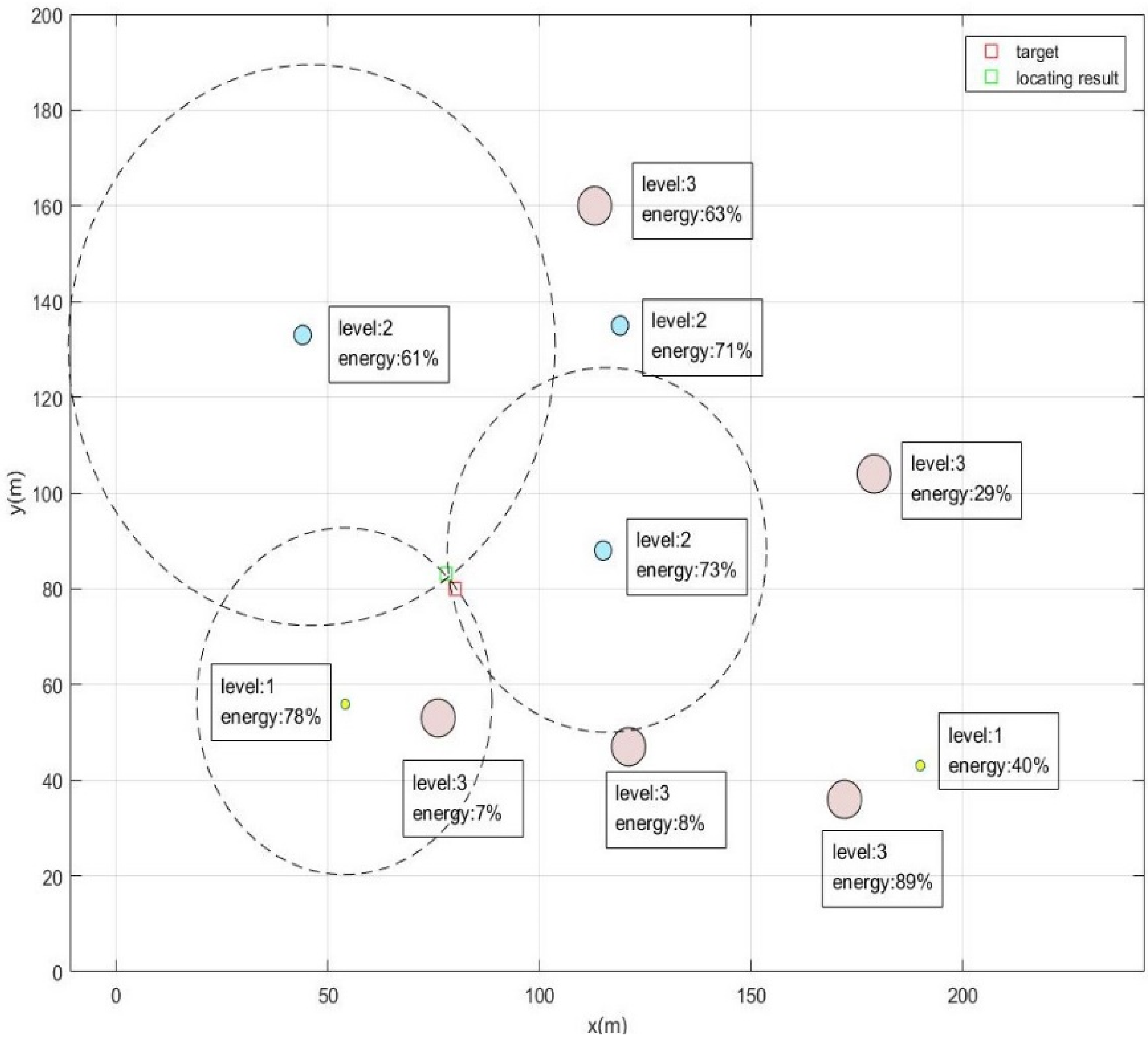


FIGURE 7. **Schematic diagram of the simulation scenario.**

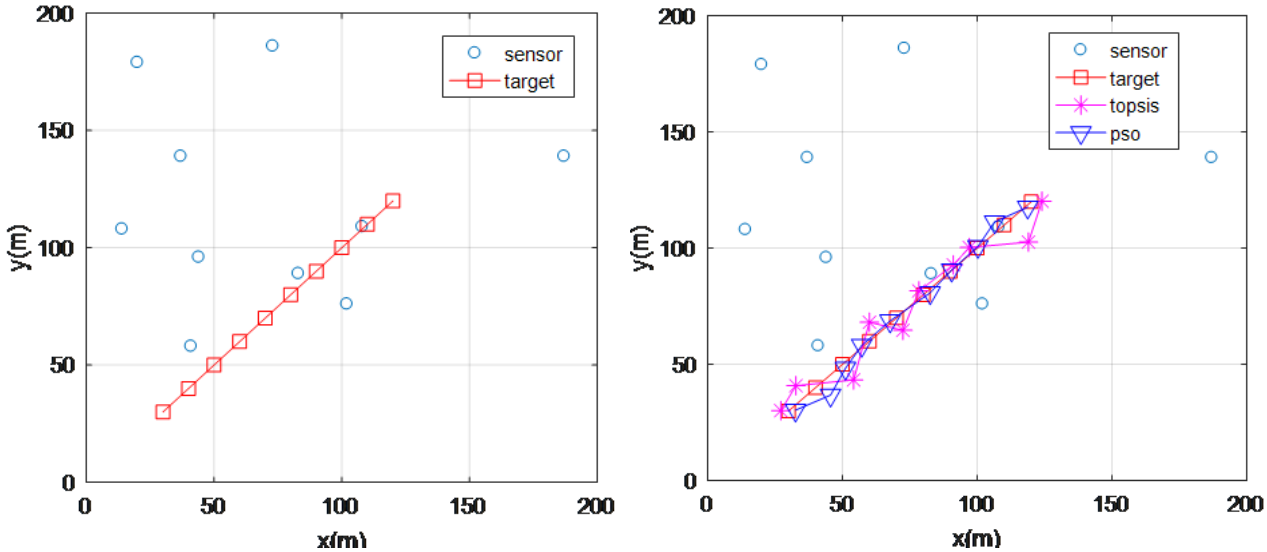
is mainly limited by the ocean's channel noise environment, so the effect of sound velocity correction is relatively insignificant. However, the results of the comprehensive shallow sea and deep sea correction show that it is necessary to consider the sound ray bending as the node selection index.

B. POSITIONING SIMULATION RESULT

FIGURE 7 shows the actual positioning process. The nodes with different location information are distributed in the scale, which are divided into first-level, second-level and third-level. The size of the circle indicates the location suspicious of the node. The red square represents the true position of the target, and the green square is subjected to the positioning result of the particle swarm node optimization algorithm. This paper compares the positioning results of different algorithms, considering the position entropy, residual energy, and single factor of sound ray bending.

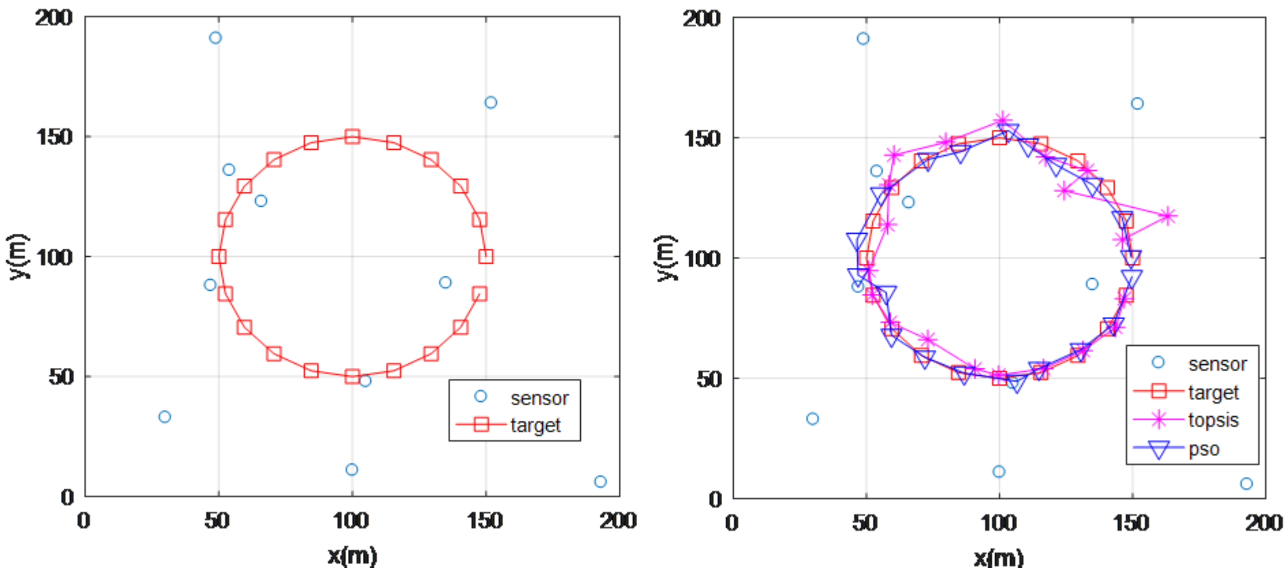
The Technique for Order Preference by Similarity to An Ideal Solution (TOPSIS) is an algorithm commonly used for multi-objective decision analysis. For each evaluation object, according to the Richter distance of the best value and the worst value of the respective analysis, calculate the corresponding reference evaluation index, and sort them pros and cons.

FIGURE 8 and 9 show the comparison of the positioning results of the target nodes moving according to $y = x$ and circular trajectories. Specifically, (a) is the actual running trajectory of the target, and (b) is the positioning trajectory by the TOPSIS algorithm and the PSO algorithm used in this paper. It can be seen that the PSO algorithm has better positioning and tracking effect than the TOPSIS.



(a) Real trajectory. (b) Calculated trajectory.

FIGURE 8. Comparison of real and calculated trajectory($y = x$).



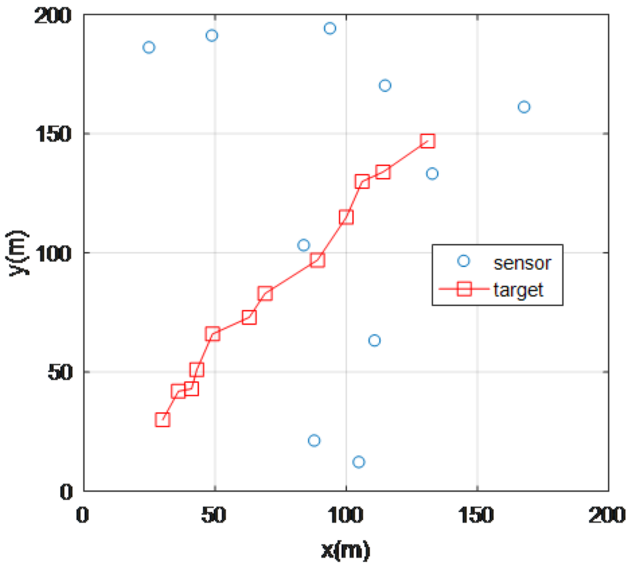
(a) Real trajectory. (b) Calculated trajectory.

FIGURE 9. Comparison of real and calculated trajectory(Circular trajectory).

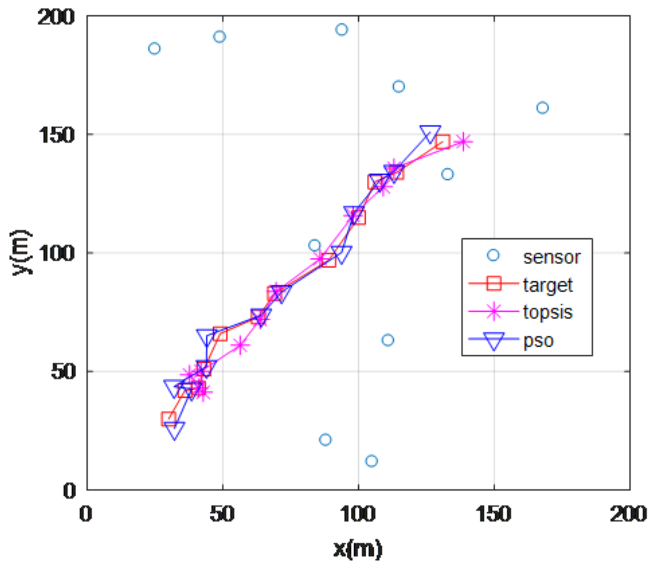
FIGURE 10 is the comparison of the actual motion trajectory and the positioning results of the target node according to random trajectory. It can be seen that the PSO algorithm can better approximate the optimal sensor combination by iteratively updating the objective function, and achieve better positioning effect.

FIGURE 11 shows the comparison of the positioning errors of different algorithms in the cumulative probability distribution. The preferred algorithm considering only the sound ray bending, residual energy and position entropy is selected for comparison. The simulation results show that the proposed algorithm makes a preferred selection from multiple dimensions, considering the influence of sound ray, node position uncertainty and energy consumption, which has higher positioning accuracy than the node optimization algorithm with single factor.

Although the performance of the two preferred algorithms is relatively close, the proposed algorithm has a slightly better effect on the positioning accuracy. Because the PSO algorithm can better approximate the optimal value of the system by setting the objective function and iterative process, which has better effect than the one-time calculation



(a) Real trajectory.



(b) Calculated trajectory.

FIGURE 10. Comparison of real and calculated trajectory(Random trajectory).

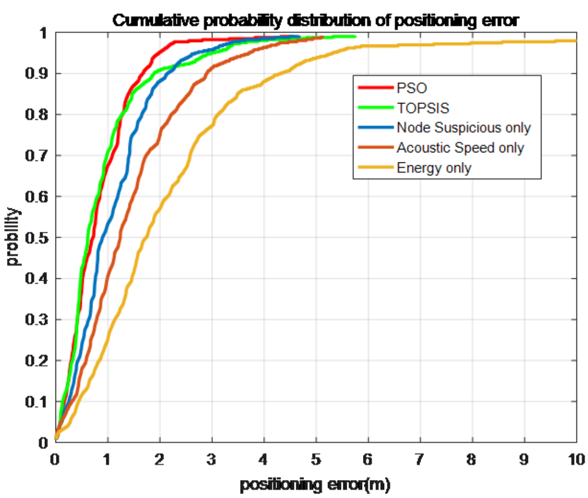


FIGURE 11. Cumulative probability distribution of positioning error.

sorting TOPSIS algorithm. It also proves the necessity of selecting and locating nodes in the process of underwater acoustic positioning.

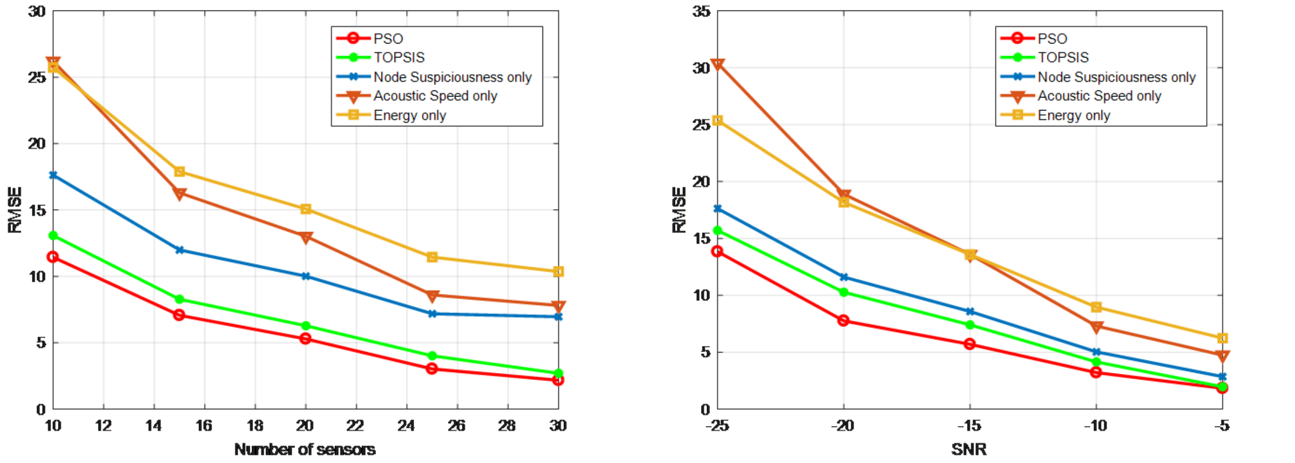
Since the underwater acoustic environment is very complex and varied, the stability of the algorithm under different conditions is also very important. FIGURE 12 a and 12 b respectively show the effects of the number of reference nodes and the noise level of the environment on the positioning accuracy.

It can be seen from FIGURE 12 a that under different algorithms, as the number of reference nodes increases, the mean square error of the target node positioning accuracy is effectively reduced. When the coverage of the reference node is low, the target node remote from reference node has to be selected to complete the positioning operation, for lower positioning accuracy. However, as the number of reference nodes continues to increase, the impact on the positioning accuracy of the target node is gradually reduced. The algorithm proposed in this paper has better performance under different reference node numbers.

As can be seen from FIGURE 12 b, when the signal-to-noise ratio is low, the positioning accuracy is poor. But with the increasement of the SNR, the positioning accuracy will be significantly improved. When the SNR reaches a certain value, the improvement of positioning accuracy is slowed down. Because the influence of the delay error caused by noise on the positioning accuracy is no longer the most important factor of error when the SNR is high. And the error at this time is mainly determined by the position uncertainty of the reference node. Therefore, the algorithm has a relatively stable performance in different SNR environments.

C. ANALYSIS OF ALGORITHM COMPLEXITY

FIGURE 13 shows the relationship between the number of sensors in the scale and the amount of calculation required by different algorithms. It can be seen from the figure that the time of calculation of different algorithms increases as the number of sensor nodes increases. Specifically, the time of calculation required by the traversal algorithm represented by the blue curve increases exponentially with the number of sensors. If the traversal method is used to obtain the optimal sensor combination, it will bring a heavy computational burden to the system. So it is not suitable for the energy-sensitive UWASN. However, the number of operation iterations of the particle swarm algorithm is very flat, which means that the amount of calculation increases slightly as the sensor node increases. Therefore, the latter is more suitable for the UWASN.



(a) Comparison under different numbers of sensors.

(b) Comparison under different SNR.

FIGURE 12. Influence of other conditions on positioning accuracy.

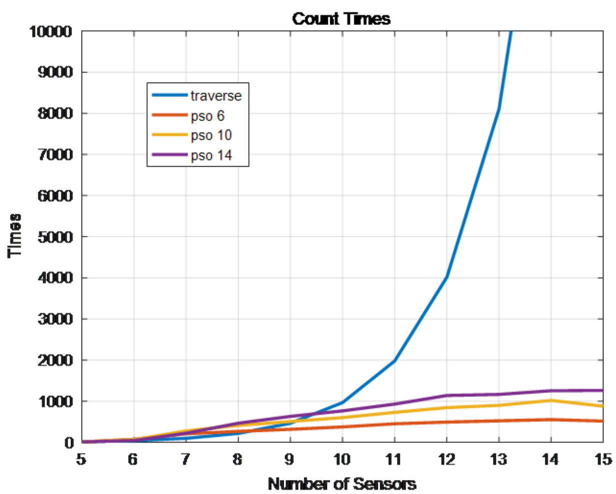


FIGURE 13. Relationship between the calculation amount and the number of sensors.

In summary, the algorithm based on PSO introduced in this paper can better approximate the theoretical optimal sensor combination, and effectively save computational cost as well as communication overhead. It is suitable for UWASN systems with relatively limited energy, and has a good practical application value.

VI. CONCLUSION

This paper focuses on improving the positioning accuracy of underwater acoustic sensor networks. It will transform the problem of positioning performance improvement of the underwater acoustic sensor network into the problem of node optimization, and design corresponding algorithms to improve the performance. The factors that can influence the node selection mainly contains the sound ray bending of single sensor capturing positioning accuracy, and the node position uncertainty, energy loss as well as collinearity which occur when multiple sensors are coordinated and we separately set a certain standard for mathematical modeling to evaluate these parameters.

Aiming at the problem of sound velocity correction, this paper analyzes the acoustic characteristics of deep sea and shallow sea by the marine measured data published by NODC, and analyzes the sound ray bending phenomenon of acoustic signals in the process of underwater acoustic environment propagation. Calculating the ratio of the actual distance between the anchor node and the target to the propagation delay for establishing an effective sound speedometer and correct the ranging error in the underwater acoustic positioning system.

In addition, this paper introduces position entropy to measure the uncertainty of node position. The position entropy is defined by estimating the number of unit areas of the node. The smaller the position entropy is, the more reliable the node is.

The energy loss function is defined by the difference between the individual sensor nodes and the transmission loss. The transmission loss is obtained by the acoustic wave transmission model and divided into diffusion loss and absorption loss. The larger the energy loss function means the more the node energy and the more suitable for positioning.

The collinearity expression is obtained according to the point-to-line distance formula. The greater the collinearity, the reasonable topology of the selected nodes and the less influence of the positioning error.

For the node redundancy scenario of positioning on UWASN, the node selection algorithm based on particle swarm optimization is proposed. Under the premise of ensuring a certain positioning accuracy, this paper comprehensively considers the various influencing factors mentioned above to select the nodes that can be selected, and iterates out the optimal sensor combination. The simulation compares the positioning accuracy of different optimization algorithms and discusses the performance of different noise environments as well as number of reference nodes. The results show that the PSO can better meet the requirements of node selection, and has the advantages of small computation and fast convergence with good practical value.

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