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A Quick Deployment Method for Sonar Buoy Detection Under the Overview Situation of Underwater Cluster Targets

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ABSTRACT Aiming at the typical problems of deploying sonar buoys in appointed sea area, this paper summarizes two problems existing in previous studies and puts forward a quick deployment method for sonar buoys detection under the overview situation of underwater cluster targets. Firstly, considering the influence of an underwater target course on target strength, the overlapping coefficient "buoy group" mode is introduced to deploy the array. And combining with the random distribution law of underwater targets in the exploration area, the mathematical optimization model for sonar buoys detection under the overview situation of underwater cluster targets is established. Then, the fitness function corresponding to the buoy deployment optimization model is defined, and the adaptive fireworks algorithm is used to solve the optimization problem for obtaining the sonar buoys deployment scheme. Finally, through the comparison and analysis of results for the seven group simulation experiments, the conclusions that are beneficial to improve the detection efficiency of the sonar buoy deployment are obtained. The proposed method can provide useful support for underwater cluster multi-target detection and the problem of counterattack underwater cluster multi-platform.

INDEX TERMS Underwater cluster targets, buoy detection, buoy network, fireworks algorithm, target strength characteristics.

I. INTRODUCTION

Swarm Intelligence (SI) technology has not only developed unprecedentedly in the aviation field but also has many applications in the underwater field. The development of UUV cluster technology has greatly promoted the diversification trend of underwater multi-agent platforms. Underwater frogman, underwater robot, UUV and other small target platforms with strong maneuverability form a huge network cooperative intelligent system, which poses a growing threat to ships. Timely detection and identification of small targets in multi-platform clusters lurking in the water and taking striking measures are essential. Therefore, it is of great military significance to detect multi-targets of underwater clusters.

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Searching, identifying and attacking underwater target platforms by military aircraft is the main form of modern anti-underwater target warfare [1]. As the main equipment for searching underwater targets on the aviation platform, the sonar buoy has the advantages of convenient carrying and deployment, and can quickly form a large-area search array. There are two basic methods of searching underwater targets by aviation platforms: called search and patrol search. Called search belongs to a secondary search. The approximate location information of the enemy target platform is known when performing the called search task. The aviation platform is required to reach the search area at the fastest speed to improve the probability of re-discovering underwater targets [2]. When a single sonar buoy searches for underwater targets, its detection range is limited, so a certain search array is usually used to search underwater targets. The number and array of sonar buoys placed determines the probability of searching and detecting targets [3]. By arranging the buoy network reasonably, the monitoring range of the sonar buoy in this area is not less than the established requirement under the premise of using the minimum number of buoys [1]. However, in the training of anti-underwater targets, experience-guided deployment is still the main method. The traditional deployment method is a simple geometric layout and does not optimize the array according to the position estimation of underwater cluster targets. It lacks a strictly theoretical basis and has large blindness, which leads to a low success rate of underwater target detection [1], [4]. Buoy optimization array is the key technology for underwater target motion detection. The selection and optimization of factors such as formation, array spacing, and number of array elements, as well as the course and speed changes of underwater targets, have a great influence on the search and detection probability of underwater targets [5]. Optimization of the array includes parameters such as formation, array spacing, and number of array elements. The parameter that measures whether the formation is optimized is the accumulative detection probability [5].

For the buoy optimization problem of underwater target detection, a mathematical model is often established based on certain assumptions, and the bionic intelligent optimization algorithm [1], [6] and its improved algorithm [4] are applied to solve the problem. Yang *et al.* comparatively studied the submarine search efficiency of a circular array, triangular array, and square array, and analyzed the influence factors of submarine initial state on submarine search efficiency [3]. Fa studied the problem of multi-base sonar array deployment under warning mode and proposed an array deployment method based on the positive n-polygon mapping, which greatly reduced the computational complexity [7]. Zhou *et al.* proposed a passive buoy network deployment method based on genetic algorithm(GA), which successfully proved that GA can effectively optimize the buoy network and improve its detection efficiency in complex underwater acoustic environment, but its ability to deal with complex situations with constraints is not strong [6]. Fan established several mathematical models of submarine search with typical geometric shapes and optimized the buoy network based on the ''optimal'' improved genetic algorithm [4]. Yan *et al.* used the genetic algorithm to solve this optimization problem, and generated a large number of buoy network samples [1]. On this basis, a neural network module for assistant decision-making of the buoy network was constructed, and the optimal buoy network pattern was trained and learned. Zeng *et al.* applied the fast non-dominant sorting genetic algorithm NSGA-II to the optimization of the buoy network [8]. Combining with buoy call-and-search tactics, the accumulative detection probability CDP of buoy network was taken as the optimization objective, and the passive omnidirectional buoy network was optimized to improve the efficiency of the buoy network. Mo *et al.* introduced a genetic algorithm into the optimization of buoy network and determined the parameters of the buoy network by reasonably selecting the relevant factors in the genetic algorithm [5]. In order to solve the jamming arraying problem of multi-aircraft cooperative suppression enemy air defense radar network in electronic warfare mission planning, Zhang *et al.* used a multi-objective particle swarm optimization algorithm to solve the multi-objective optimization model [9]. Sun considered the influence factors such as the overlap coefficient of the buoy group and the influence of the target course on echo signal strength and applied the Monte Carlo method to obtain a better sonar buoy deployment formation [2].

The above research results have achieved good results under certain assumptions and mathematical models, but there are still two problems: ① The buoy network is based on the mathematical model established under the assumption of simple regular geometric configuration, which fails to use the detection efficiency of the buoy network. ② It is unreasonable to blindly regard the standard circular domain as the searching area for detecting underwater targets without considering the target strength characteristics and the influence of the target course on the buoy detection distance. In view of this, this paper combines the previous research results to focus on the improvement of these two problems. Referring to the processing method of considering the target course in [2], this paper used the ''butterfly-type'' target strength detection domain as the search area and introduced the overlapping coefficient ''buoy group'' mode to arrange the buoy network. At the same time, combined with the random distribution law of the underwater target in the search area, the mathematical optimization model of the buoy network under the target situation is established. Then the adaptive fireworks algorithm is used to solve the optimization problem, and the sonar buoy network scheme under the condition of underwater cluster targets situation is obtained.

This paper is divided into five sections. The first section introduces the research background of the article, summarizes the research progress of predecessors, puts forward the problems existing in the research, and summarizes the research ideas of this paper. The second section establishes a mathematical optimization model of buoy deployment under the overview of the target situation. This part establishes an effective optimization model for two problems existing in previous studies. The third section introduces the adaptive fireworks algorithm and defines the fitness function corresponding to the optimization model in the second section. The fourth section is simulation and experimental verification. The fifth section summarizes the work of this paper and puts forward the shortcomings in the research which provides guidance for the follow-up research.

II. MATHEMATICAL OPTIMIZATION MODEL OF BUOY DEPLOYMENT UNDER OVERVIEW THE TARGET SITUATION

In view of the two problems existing in the previous research summarized in the first part, this paper referred to the processing method of considering the target course in [2], used the ''butterfly-type'' target strength detection domain as the search area, and introduced the overlapping coefficient ''buoy group'' mode to arrange the buoy network. At the same time, combined with the random distribution law of the underwater target in the search area, the mathematical optimization model of the buoy network under the target situation is established.

For a single-static sonar buoy detection system, the active sonar is a combination of receiving and transmitting. It is easy to expose its own position while detecting the enemy's position during combat. Although the passive sonar has good concealment, it has limited detection ability for quiet targets and easy to lose targets[10]. Therefore, the active detection system of multistatic sonar buoy with a combination of receiving and transmitting is adopted in this paper, as shown in Fig. 1. When combatting in the deep sea, the acoustic source and the receiving array are arranged separately, and the receiving array is composed of passive sonar buoy nodes. The passive sonar buoy receiving node is placed far away from the acoustic source transmitting node to form a certain range of warning sea areas, which can achieve the purpose of long-distance cooperative detection [11]. This paper studies the deployment of passive sonar buoy receiving nodes.

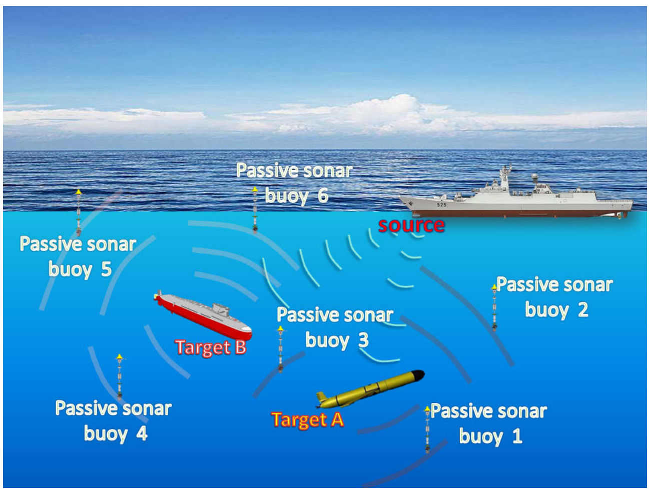


FIGURE 1. Active detection system of sonar buoy with separate transmitter and receiver.

A. INITIAL POSITION DISPERSION OF UNDERWATER CLUSTER TARGETS

The initial position of the underwater cluster targets are derived from the underwater target location information discovered by the aviation search platform itself or other intelligence sources. According to the central limit theorem, a Cartesian coordinate system (x, y) is established. The initial position $X(x_0, y_0)$ in the Cartesian coordinate system obeys a two-dimensional normal distribution, ie $X \sim N(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$ [2]. At this time, the joint probability function of the initial position of an underwater target is:

$$
\begin{aligned}
f(x_0, y_0) &= \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \\
&\quad \cdot e^{-\frac{1}{2(1-\rho^2)}\left[\frac{(x_0-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_0-\mu_1)(y_0-\mu_2)}{\sigma_1\sigma_2} + \frac{(y_0-\mu_2)^2}{\sigma_2^2}\right]} \\
&\quad (-\infty < \mu_1, \mu_2 < +\infty; \sigma_1, \sigma_2 \geq 0; -1 < \rho < 1) \qquad (1)
\end{aligned}
$$

where u_1 and u_2 are the mean values of horizontal and vertical coordinates of the initial position of underwater cluster targets. σ_1 and σ_2 are the standard deviations of horizontal and vertical coordinates of the initial position of underwater cluster targets. ρ is the correlation coefficient of horizontal and vertical coordinates of the initial position of underwater cluster targets. According to the 3σ principle of normal distribution, that is $P(\mu - 3\sigma < X \leq \mu + 3\sigma) = 99.7\%$. It is assumed that the underwater cluster targets are distributed in a rectangular region with a length of l and width of w. In order to make the initial position of the underwater cluster targets substantially distributed in the rectangular area, $u_1 = l/2$, $u_2 = w/2$, $\sigma_1 = l/6$, $\sigma_2 = w/6$.

B. INITIAL COURSE DISTRIBUTION OF UNDERWATER CLUSTER TARGETS

The course $\Theta(\theta)$ of the underwater cluster targets obeys a uniform distribution, that is, $\Theta \sim U[a, b]$[2]. The joint probability function of the initial course of the underwater target is:

$$
f(\theta) = \begin{cases} \dfrac{1}{b-a}, & a < \theta < b \\ 0, & else \end{cases} \qquad (2)
$$

One of the simulation environments studied in this paper is set as follows: The target distribution range of the underwater cluster is set in the rectangular region of [0-30km, 0-20km]. The initial position of underwater cluster targets obeys the two-dimensional normal distribution of $X \sim N(15, 10, 25, \frac{100}{9}, 0)$, and the initial course of underwater cluster targets obeys the uniform distribution $\Theta \sim U[0, 2\pi]$. The initial situation of a group of underwater cluster targets is shown in **Fig. 2**.

The green dotted rectangular frame in **Fig. 2** is the distribution range of the underwater cluster targets. The red $*$ points are the initial position of the underwater cluster targets, and the blue solid lines are the course direction line of the underwater cluster targets.

C. EFFECTIVE REGION OF BUOY DEPLOYMENT FOR TARGETS BEING DETECTED IN CONSIDERING OF COURSE EFFECT

For the effective detection area of sonar buoys to search underwater targets, most scholars blindly regard the standard circle as the detection area of underwater targets, without combining the target strength characteristics and considering the influence of target course on the buoy detection distance. Therefore, this paper draws on the method in [2] which used

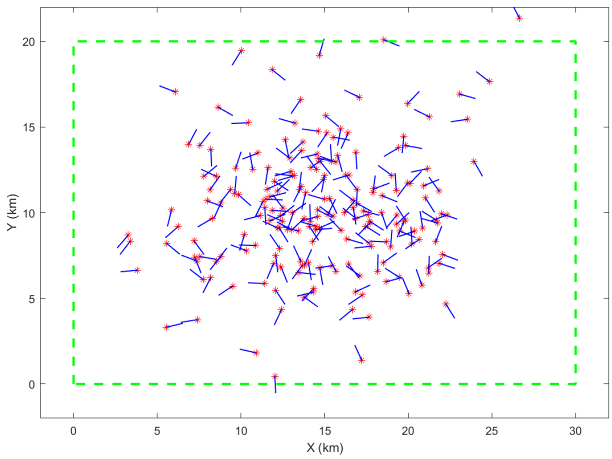


FIGURE 2. Initial situation figure of underwater cluster targets satisfying the distribution law.

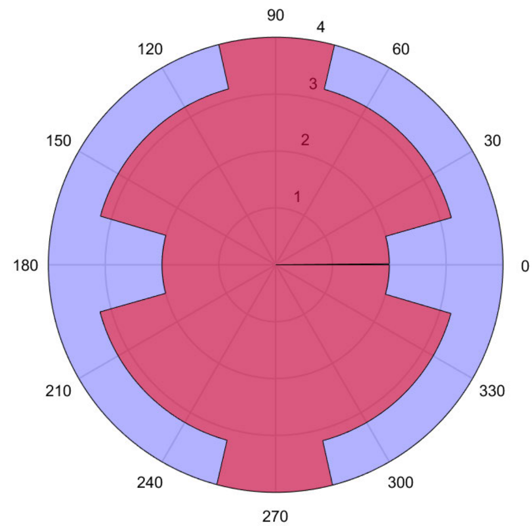


FIGURE 3. Effective deployment region of the buoy for a single target being detected when considering the influence of the course.

the "butterfly-type" target strength detection domain as the search area.

When sonar buoys are searching for underwater targets, the buoys will judge the position of underwater targets through the target echo signal. The intensity of the echo signal which is mainly related to the target course represents the target strength. Because the search radius of a sonar buoy varies with the course of the underwater target, its detection area is not an ideal circular domain. If this situation is not taken into account in the deployment of the buoy network, the false alarm rate of the buoy network will increase, and the probability of searching for underwater targets will decrease.

When the echo signal is reflected from the longitudinal direction of a target, the signal is the strongest, and when the echo signal is reflected from the axial direction of a target, the signal is the weakest [12], [13]. According to the different courses of a submarine, the target strength presents a "butterfly-type" change. In order to facilitate the research, the different angle between the course of underwater target and buoy point is used to define the buoy detection distance in the simulation analysis of this paper. In this paper, assuming that the angle φ between the course of the underwater target and the position of the buoy is $0°\sim15°$ and $165° \sim 180°$, the underwater target detection distance of the sonar buoy is only 0.5 times the maximum detection radius. When the angle φ is $15° \sim 75°$ and $105°\sim165°$, the underwater target detection distance of the sonar buoy is only 0.8 times of the maximum detection radius. When the angle φ is $75° \sim 105°$, the underwater target detection distance of the sonar buoy will reach the maximum detection radius. The maximum detection radius of the sonar buoy for an underwater target is 4 *km*. Based on this assumption, the effective deployment region of the buoy for a single target being detected when considering the influence of the course is as shown in **Fig. 3**. The blue circular domain in the figure is the effective buoy deployment region when a single target is detected without considering the influence of the course on echo signal intensity of underwater target, and the red coverage area is the effective buoy deployment region when a single target is detected considering the influence of the course. The course of the target is the solid black line (0° direction) drawn from the target centroid along the radial direction. As can be seen from the previous introduction, when the sonar buoy is placed in the red area, the target can be detected, and when the sonar buoy is placed in the blue area, the target cannot be detected.

D. MATHEMATICAL SIMULATION MODEL OF BUOY NETWORK FOR DETECTING UNDERWATER CLUSTER TARGETS

1) ACCUMULATIVE DETECTION PROBABILITY MODEL

The simulation environment studied in this paper is that the underwater cluster targets are randomly distributed in a rectangular sea region according to a certain distribution law. The aviation platform carries a certain number of sonar buoys to search and detect the underwater cluster targets in this area according to their own equipment performance constraints. By reasonably deploying a buoy network, the accumulative detection probability of the sonar buoy for cluster targets in this region is not less than the established requirement on the premise of using the minimum number of buoys.

According to the above task scenario, a mathematical model for calculating the accumulative detection probability is constructed. Assuming that the rectangular sea region Φ has a length of l and a width of w, and the maximum detection radius of the sonar buoy for the underwater target is r. By deploying buoys, the probability of underwater cluster targets being detected by buoys is not less than P_0.

Assuming that the probability of the underwater target at arbitrary coordinate (x,y) in the region Φ is $p(x,y)$, then the total probability P_Φ of the underwater target in this region is:

$$P_\Phi = \int_0^l \int_0^w p(x, y)dxdy \tag{3}$$

Finally, by deploying n sonar buoys, the accumulative detection probability of the underwater targets is P. According to the task objective whose accumulative detection probability of buoy detecting underwater cluster target is not less than P_0, there should be:

$$\frac{P}{P_\Phi} \geq P_0 \tag{4}$$

In this paper, the grid method is used to calculate the accumulative detection probability P of detecting underwater targets. The specific steps are as follows:

(1) Divide the region Φ into square grids with side length d_0, then:

$$n_a = round(\frac{l}{d_0}), n_b = round(\frac{w}{d_0}) \tag{5}$$

Among them, *round*( ) is rounded integer operation, n_a is the number of long-side grids in the search area, and n_b is the number of wide-side grids in the search area.

(2) Use parameter ξ to mark whether the target located in each grid is within the detection range of a certain buoy. The criterion and judgment standard is whether n sonar buoys are located in the effective buoy deployment region of the single target to be detected when considering the influence of the course. If it is in the effective deployment region, then $\xi = 1$; otherwise, $\xi = 0$. As shown in **Fig. 4**.

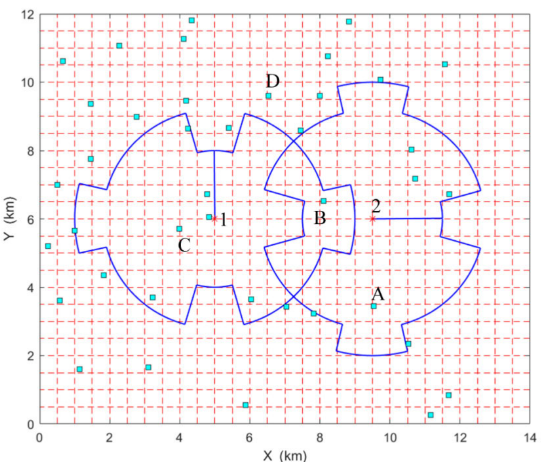


FIGURE 4. Schematic diagram of criterion and judgment standard for buoy detection.

As shown in **Fig. 4**, when the buoy is located at point A, the sonar buoy can detect the target 2, at which time $\xi = 1$. When the buoy is located at point B, the sonar buoy can simultaneously detect targets 1 and 2, where $\xi = 1$. When the buoy is located at point C, the sonar buoy can detect the target 1, when $\xi = 1$. When the buoy is located at point D, the sonar buoy can not detect targets 1 and 2, at which time $\xi = 0$.

(3) Calculate the approximate value of P.

$$P = \sum_{i=1}^{n_a} \sum_{j=1}^{n_b} \xi_{i,j} p(x_i, y_j) d_0^2 \tag{6}$$

where $\xi_{i,j}$ is the parameter value of ξ corresponding to the grid of the i-th row and the j-th column, and $p(x_i, y_j)$ is the probability that the underwater target is at the coordinate (x_i, y_j) corresponding to the grid of the i-th row and the j-th column.

Through the above steps, the accumulated detection probability value P of n sonar buoy network for detecting underwater targets can be obtained.

2) MINIMUM BUOY DEPLOYMENT QUANTITY MODEL

According to the operational objectives, it is necessary to complete the task of searching underwater cluster targets with as few buoys as possible. In the case where the underwater cluster target distribution law is unknown, it is generally assumed that underwater cluster targets are uniformly distributed in the region Φ, that is, $p(x, y) = p_0$. According to the empirical formula of the minimum buoy number in reference [1], there are:

$$n = ceil(\frac{lwP_0}{\pi r^2}) \tag{7}$$

where, *ceil*( ) is the upward rounding operation, l and w are respectively the length and width of rectangular sea area where underwater cluster targets are distributed, P_0 is the accumulative detection critical probability of underwater cluster targets detected by buoys, and r is the maximum detection radius of sonar buoys for detecting underwater targets.

3) "BUOY GROUP" DEPLOYMENT MODE WITH OVERLAPPING COEFFICIENT

When deploying a sonar buoy network, the two buoys can neither be too far apart from each other nor overlap the detection area in a larger area. Otherwise, there will be a large probability of missed detection between buoys or repeated detection of the same target, which will not give full play to the detection efficiency of the buoy network. Referring to the reference [2], the concept of the "buoy group" with an overlapping coefficient is introduced. The two buoys act as a buoy group, and the overlapping coefficients indicate how many coincidences exist between the "buoy group" buoys. The maximum detection radius of sonar buoy for underwater target is r, and the distance between buoy A and buoy B is $k_0 \cdot r$. k_0 is the overlap coefficient. It can be seen that the coordinates of two buoys are (x_{s_i}, y_{s_i}) and $(x_{s_{i+1}}, y_{s_{i+1}})$ respectively, and the overlap coefficient is the ratio of the coordinate distance $d_{s_{i,i+1}}$ between two buoys to the maximum detection radius r of sonar buoys to the underwater target:

$$k_0 = \frac{d_{s_{i,i+1}}}{r} = \frac{\sqrt{(x_{s_{i+1}} - x_{s_i})^2 + (y_{s_{i+1}} - y_{s_i})^2}}{r} \tag{8}$$

As shown in **Fig. 5**, (a) is the positional relationship between two buoys when the buoy group overlap coefficient k_0 =1 and (b) is the positional relationship between two buoys when the buoy group overlap coefficient k_0 =2. (a) and (b) are the limit cases of the overlap coefficient, and (c) is the general case of

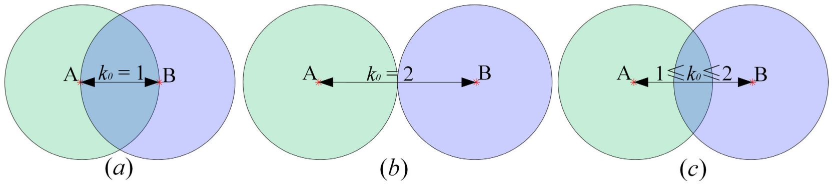


FIGURE 5. "Buoy group" deployment mode with overlapping coefficient.

the positional relationship between two buoys. The range of the overlap coefficient is $1 \leq k_0 \leq 2$.

4) OPTIMIZATION MODEL OF BUOY NETWORK FOR DETECTING UNDERWATER CLUSTER TARGETS

It can be seen from the above introduction that under the initial position and course of underwater cluster targets being known, the probability optimization model of the sonar buoy network detecting underwater cluster targets can be expressed as

$$\begin{cases} \max P = f(\theta, X_S, X_T) \\ s.t. \begin{cases} P/P_\Phi \geq P_0 \\ 0 \leq \theta \leq 2\pi \\ 0 \leq x_s \leq l \\ 0 \leq y_s \leq w \\ 1 \leq k_0 \leq 2 \end{cases} \end{cases} \tag{9}$$

where, X_S is the matrix of sonar buoy network position coordinate series (x_s, y_s), and X_T is the matrix of underwater cluster target position coordinate series (x_t, y_t). A only indicates that the accumulative detection probability P of detecting underwater targets is related to the course of underwater targets, the position coordinate matrix of sonar buoy network and the position coordinate matrix of underwater cluster targets.

The optimization model is quickly solved by the adaptive fireworks algorithm introduced in section 3 to obtain the position coordinate matrix of the sonar buoy network, which is the sonar buoys deployment scheme.

III. ADAPTIVE FIREWORKS ALGORITHM

Based on the mathematical optimization model of buoy network under the overview situation being known established in section 2, this section used the adaptive fireworks algorithm to solve the optimization problem, and obtained the sonar buoy network scheme.

Fireworks algorithm is a new swarm intelligent algorithm, which has the self-adjusting mechanism with local search ability and global searchability. In addition, the introduction of Gaussian variation sparks can further increase the diversity of the population [14], [15].

Based on the shortcomings and performance deficiencies of each operator of the basic fireworks algorithm, the enhanced fireworks algorithm puts forward the corresponding improvement strategies and methods. Based on the enhanced fireworks algorithm, the adaptive fireworks algorithm proposed an adaptive explosion radius mechanism.

A. BASIC FIREWORKS ALGORITHM

The basic principle of the fireworks algorithm is that if the fireworks' corresponding fitness function value is smaller, then the number of fireworks explosion spark is larger and the explosion amplitude is smaller. Conversely, the number of fireworks explosion sparks is smaller and the explosion amplitude is greater. Fireworks algorithm consists of four parts: explosion operator, mutation operator, mapping rule and selection strategy.

1) EXPLOSION OPERATOR

a: EXPLOSION INTENSITY

In the fireworks algorithm, the number of sparks generated is as follows:

$$S_i = m \frac{Y_{\max} - f(x_i) + \varepsilon}{\sum_{i=1}^{N} (Y_{\max} - f(x_i)) + \varepsilon} \tag{10}$$

where, S_i is the number of sparks generated by the i-th fireworks; m is a constant used to limit the total number of sparks generated; Y_{max} is the adaptive value of the worst individual in the current population; $f(x_i)$ is the fitness value of individual x_i; ε is an extreme small constant used to avoid the denominator becoming zero.

In order to limit the number of fireworks explosion sparks being too large or too small, we set the following restrictive formulas for calculating the number of sparks generated of each firework:

$$\widehat{s_i} = \begin{cases} round(a_0 \cdot m), S_i < a_0 \cdot m \\ round(b_0 \cdot m), S_i > b_0 \cdot m, a_0 < b_0 < 1 \\ round(S_i), otherwise \end{cases} \tag{11}$$

where, $\widehat{s_i}$ is the number of sparks that the i-th firework produced, and *round*( ) is the rounded integer function. a_0 and b_0 are the given constants.

b: EXPLOSION AMPLITUDE

The formula for calculating the range of fireworks explosion amplitude is as follows:

$$A_i = A\_\min + (A\_\max - A\_\min) \cdot \frac{f(x_i) - Y_{\min} + \varepsilon}{\sum_{i=1}^{N} (f(x_i) - Y_{\min}) + \varepsilon} \tag{12}$$

where A_i is the explosion amplitude range of the i-th fireworks. The explosion spark will randomly move within this range, but can't go beyond this range. A_max and A_min are the maximum and the minimum explosion amplitude respectively, which is a constant. The parameter Y_{min} is the fitness value of the best individual in the current population. The meaning of $f(x_i)$ and the parameter ε is the same as that in equation (10).

c: MOVING OPERATION

The moving operation is to move each dimension of the fireworks:

$$\Delta x_i^k = x_i^k + rand(0, A_i) \tag{13}$$

where, $rand(0, A_i)$ represents a uniform random number generated within the amplitude A_i.

2) MUTATION OPERATOR

x_i^k indicates the position of the n-th individual in the k-th dimension, and the calculation method of Gaussian variation is expressed as follows:

$$x_i^k = x_i^k \times g \tag{14}$$

where g is a Gaussian distribution random number with a mean of 1 and a variance of 1.

3) MAPPING RULE

The modular computing mapping rules are used here, and the formula is expressed as follows:

$$x_i^k = x_{\min}^k + \left|x_i^k\right| \%(x_{\max}^k - x_{\min}^k) \tag{15}$$

where x_i^k denotes the position of the i-th individual beyond the boundary in the k-th dimension. $x_{\max}^k$ and $x_{\min}^k$ respectively represent the upper and lower bounds on the boundary of the k-th dimension. % represents a modular operation.

4) SELECTION STRATEGY

In the fireworks algorithm, the Euclidean distance is used to measure the distance between any two individuals:

$$R(x_i) = \sum_{j=1}^{K} d(x_i, x_j) = \sum_{j=1}^{K} \left\|x_i - x_j\right\| \tag{16}$$

where $d(x_i \cdot x_j)$ represents the Euclidean distance between any two individuals x_i and x_j. $R(x_i)$ denotes the sum of distance between x_i and other individuals. $j \in K$ means that the j-th position belongs to the set K which is the positions set of the sparks produced by the explosion operator and the Gaussian mutation.

Use the roulette method to choose individuals. The probability of each individual being selected is denoted by $p(x_i)$:

$$p(x_i) = \frac{R(x_i)}{\sum_{j \in K} R(x_j)} \tag{17}$$

It can be seen from the above formula, individuals which farther away from the other individuals will have more opportunities to become the next generation of individuals. This selection method ensured the population diversity of the fireworks algorithm.

B. ENHANCED FIREWORKS ALGORITHM

The basic principle of the fireworks algorithm is that if the fireworks corresponding fitness function value is smaller, the enhanced fireworks algorithm proposed the corresponding improvement strategies and methods basing on the defects and insufficient performance of the various operators in the basic fireworks algorithm.

1) MINIMUM EXPLOSION RADIUS DETECTION STRATEGY

The minimum explosion radius detection strategy is introduced in the enhanced fireworks algorithm. $A_{min,k}$ is the detection threshold with the lowest explosion radius at the k-th dimension:

$$A_{ik} = \begin{cases} A_{\min,k}, & A_{i,k} < A_{\min,k} \\ A_{ik}, & otherwise \end{cases} \tag{18}$$

where A_{ij} denotes the explosion radius of the fireworks i on the k-th dimension. In the selection of $A_{min,k}$, the non-linear decreasing explosive radius detection strategy is adopted. That is:

$$A_{\min,k}(t) = A_{init} - \frac{A_{init} - A_{final}}{evals_{\max}} \sqrt{(2evals_{\max} - t)t} \tag{19}$$

where t is the evaluation number of the current iteration. $evals_{\max}$ is the maximum assessment number. A_{init} and A_{final} are respectively the initial and final detection values of the explosion radius.

2) NEW TYPE OF EXPLOSION SPARK GENERATION

The dimension selection methods of the enhanced fireworks algorithm and the basic fireworks algorithm are different. That of the enhanced fireworks algorithm is

$$z^k = round(U(0, 1)), \quad k = 1, 2, \ldots, D$$

where $U(0,1)$ denotes a random number uniformly distributed in the interval of [0,1]. In other words, the number of dimensions selections is distributed in the form of binomial distribution in [0-D]. However, the dimension selection methods of the basic fireworks algorithm is $z = round\ (D \times U(0, 1))$, and the shifting distances produced on each dimension are equal.

3) NEW GAUSSIAN MUTATION OPERATOR

The new Gaussian mutation operator is proposed for the enhanced fireworks algorithm. The new Gaussian spark is calculated as follows:

$$x_{ik} = X_{ik} + (X_{BK} - X_{ik}) \times g \tag{20}$$

where g is a Gaussian random variable with a mean of 0 and a variance of 1. X_{ik} indicates the position of the i-th individual in the original Gaussian variation spark on the k-th dimension. X_{bk} is the position information of the fireworks in the k-th dimension whose fitness value is the best in the current fireworks population.

4) NEW MAPPING RULES

The enhanced fireworks algorithm proposed a random mapping rule, which uses the following formula to map the spark exceeded the boundaries:

$$x_{ik} = x_{\min}^{k} + U(0,1) \cdot (x_{\max}^{k} - x_{\min}^{k}) \tag{21}$$

where $U(0,1)$ is a uniformly distributed random number in the interval of [0,1].

5) ELITE-RANDOM SELECTION STRATEGY

In the basic fireworks algorithm, the selection strategy is based on the distance variable. However, since this selection strategy requires the Euclidean distance matrix between any two points in each generation of constructed populations. This will lead to a great time consumption for the basic fireworks algorithm. Therefore, an elite-random selection strategy is proposed, in which the individual with the best fitness value is selected firstly, and then the random selection strategy for other fireworks is adopted. After the fireworks and Gaussian variation sparks are generated in the fireworks population, enhanced fireworks algorithm chooses the individuals (elite) with lowest fitness value from these fireworks, explosion sparks and Gaussian variation sparks as fireworks of the next generation fireworks population firstly, and then select randomly from the set of rest fireworks.

C. ADAPTIVE FIREWORKS ALGORITHM

Based on the enhanced fireworks algorithm, an adaptive explosion radius mechanism, namely the minimum radius checking mechanism, is proposed to prevent the optimal fireworks from having a radius of zero. The core idea of the adaptive explosion radius mechanism is to use the spark that has been generated to calculate the explosion radius of the optimal fireworks. Use the information obtained from this generation to calculate the radius of the optimal firework in the next generation by.

In order to calculate the adaptive radius, an individual of and the distance between it and the optimal individual is used as the radius of the next generation explosion. The selected individual satisfies the following two conditions:

① The fitness value is worse than the fireworks of this generation.

② The distance to the optimal individual is the shortest among the individuals satisfying ①. That is:

$$\hat{s} = \arg\min_{s_i}(d(s_i, s^*)) \tag{22}$$

The following conditions are satisfied:

$$f(s_i) > f(X) \tag{23}$$

where s_i represents all sparks generated by fireworks. s^* represents the individual with the best fitness in all sparks and fireworks. X denotes fireworks; d is a measure of a certain distance.

In order to further slow down the convergence rate for improving the global searchability, the adaptive radius being calculated above is multiplied by a specific coefficient. According to experience, take $\lambda = 1.3$.

Taking into account the number of sparks in each explosion is limited, it used a simple smooth mechanism to reduce the impact of particularly bad luck. The calculated adaptive radius and the explosion radius of this generation are taken as the explosion radius of the next generation.

D. ESTABLISH FITNESS FUNCTION

The basic principle of the fireworks algorithm is that if the fireworks corresponding fitness function value is smaller,

Before using the adaptive fireworks algorithm, it is necessary to determine the objective function first which is the form of fitness function [16]–[18]. After the searching region of buoys is discretized by the grid method, the fitness function P (accumulative detection probability of detecting underwater targets) can be expressed as the ratio of the number of targets detected in the buoy-searching region to the total number of underwater cluster targets in this region. The adaptive function algorithm is shown in **Fig. 6**.

Input parameters: position coordinate matrix (X_S) of sonar buoy, position coordinate matrix (X_T) of underwater cluster target, course angle matrix (Θ_T) of underwater cluster targets
J=[]; % J is used to record the detectable target number
for i=1: Number of buoys deployed
  for j=1: Number of underwater cluster targets
    Calculate the angle $\varphi_{i,j}$ between the position coordinate line of the i-th buoy and the j-th underwater target and the course line of the target;
    if $0° \le \varphi_{i,j} \le 15°$ or $165° \le \varphi_{i,j} \le 180°$
      if The linear distance between the i-th buoy and the j-th underwater target $d_{i,j} \le 0.5$ times the maximum detection radius
        J=[J,j];
      end
    elseif $15° \le \varphi_{i,j} \le 75°$ or $105° \le \varphi_{i,j} \le 165°$
      if The linear distance between the i-th buoy and the j-th underwater target $d_{i,j} \le 0.8$ times the maximum detection radius
        J=[J,j];
      end
    else
      if The linear distance between the i-th buoy and the j-th underwater target $d_{i,j} \le$ the maximum detection radius
        J=[J,j];
      end
    end
  end
end
Counting the number m that is non-repetitive numbered in the detectable target number set J;
Fitness function P (the total successful probability in detecting underwater targets) = m/ number of underwater cluster targets;

FIGURE 6. Algorithm of fitness function.

IV. VERIFICATION OF SIMULATION EXPERIMENTS

In order to verify the rationality and validity of the mathematical optimization model of buoy network under the target situation being knowing established in section 2 and the algorithm proposed in section 3, the simulation experiments verification were carried out in seven simulation environments, and five groups of simulation experiments were carried out in each simulation environment.

The main parameters of simulation environments need to be set are: the length l of the rectangular search region, the width w of the rectangular search region, the total number of underwater cluster targets, the probability threshold P_0 of underwater targets being detected successfully, the number of fireworks owned by each generation of fireworks algorithm, the number of sparks generated by each fireworks, the number of Gauss sparks generated by each firework, etc.

The simulation experiments were conducted based on the Matlab R2017a software platform. The simulation computer is equipped with an Intel(R) Core(TM) i5-5200U, 2.20 GHz CPU, 4.00GB of memory, and a 64-bit Windows 8 Ultimate operating system.

In order to verify the effectiveness and superiority of the adaptive fireworks algorithm (AFWA) proposed in this paper in solving the sonar buoy network deployment problem, the AFWA algorithm is compared with the classical ant colony algorithm (ACO) and particle swarm algorithm (PSO) in this paper. Fig. 7 shows the buoy network deployment results obtained under the three algorithms when the underwater cluster targets are subject to uniform distribution. Fig. 8 to 13 show the buoy network deployment results obtained under the three algorithms when the underwater cluster targets are subject to two-dimensional normal distribution. The corresponding results of each algorithm in each figure are the representative deployment scheme results of the five groups of simulation experiments under this environment. The main parameter settings and statistical results in the seven simulation environments are shown in TAB 1. Since the fourth simulation environment is to study the influence of the adaptive fireworks algorithm parameters on the deployment scheme, the comparison test under the simulation environment is not carried out when the comparison verification simulation experiments of the three algorithms are performed. The statistical results of the AFWA, ACO and PSO algorithm comparison verification simulation experiments under the six environments are shown in TAB. 2.

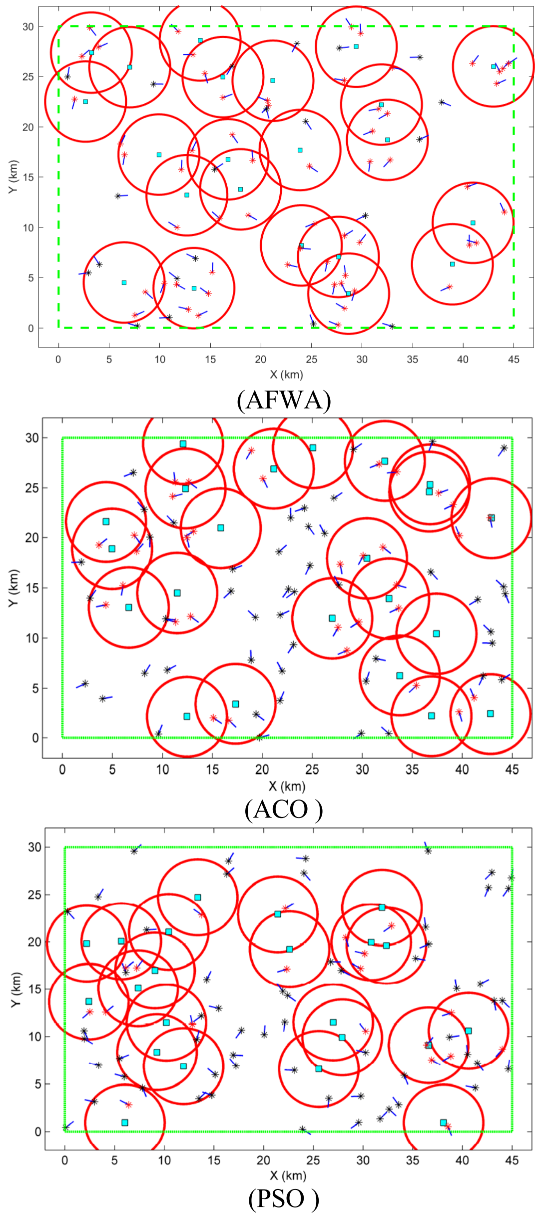


FIGURE 7. **Five sets of simulation results corresponding to the simulation environment 1.**

Comparing the deployment scheme with AFWA algorithm in **Fig. 7**, **Fig. 8** and the results of the simulation environment 1 and 2 in **Tab. 1**, it can be seen that under the same experimental simulation environment parameters, the distribution law of underwater cluster targets obeyed, that is, the initial position of the underwater cluster targets will have a great impact on the sonar buoy deployment. When the number of underwater targets and sonar buoys remains unchanged, the distribution of underwater targets obeying the uniform distribution law is dispersed in the search domain, while the underwater targets obeying the two-dimensional normal distribution law are more concentrated in the search domain. When the distribution of underwater targets is dispersed, the array of sonar buoys in this area will be also dispersed. At this time, the number of underwater targets that can be detected by a single sonar buoy will be smaller, and the probability of missed detection will be greater. Therefore, the average accumulative detection probability P of underwater targets in the five simulation experiments will be lower. When the distribution of underwater targets is concentrated, the adaptive fireworks algorithm is easy to fall into the local optimal solution when searching for the optimal sonar buoy placement points in the search domain. This will result in a longer calculation time for offspring sparks to jump out of the local search range to find the optimal solution. Therefore, under the same experimental simulation environment parameters, the more dispersed the distribution of underwater cluster targets, the lower the average accumulative

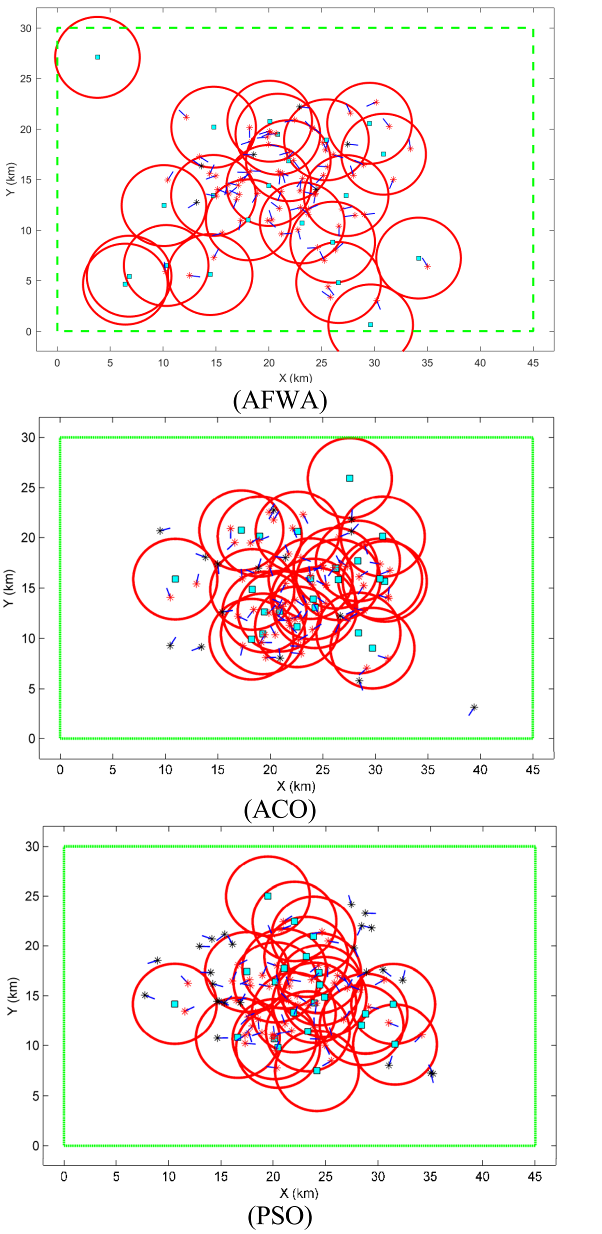


FIGURE 8. Five sets of simulation results corresponding to the simulation environment 2.

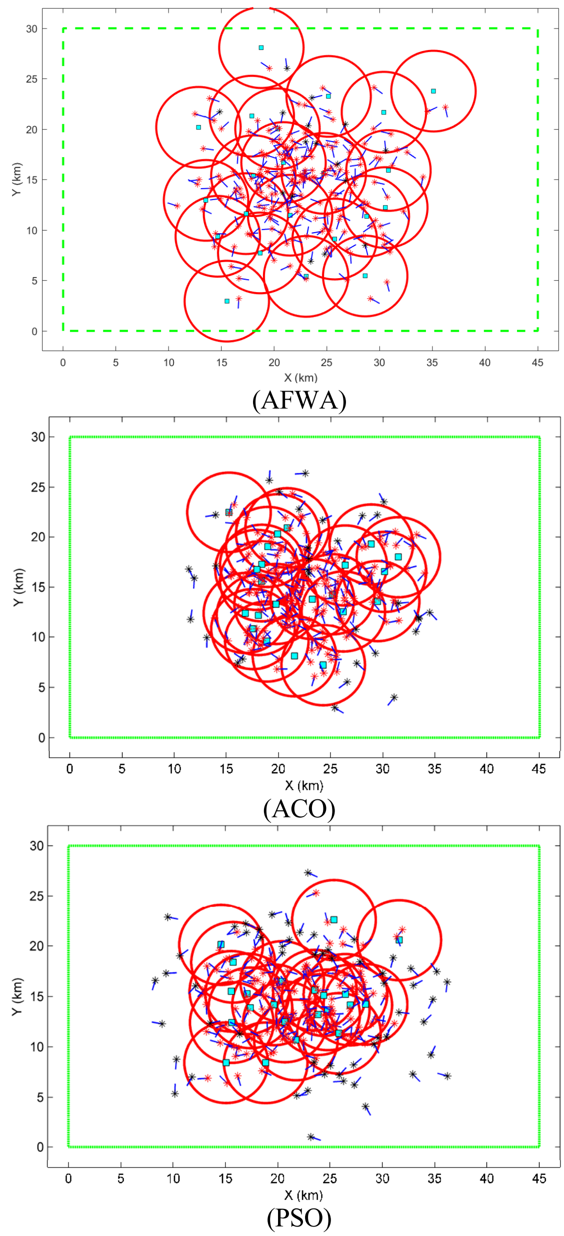


FIGURE 9. Five sets of simulation results corresponding to the simulation environment 3.

detection probability P of underwater targets. And the more concentrated the distribution of underwater cluster targets, the higher the average accumulative detection probability P of underwater targets, but the longer the calculation time.

Comparing the deployment scheme with AFWA algorithm in **Fig. 8**, **Fig. 9** and the results of the simulation environment 2 and 3 in **Tab. 1**, it can be seen that in the same search region, the number increase of underwater cluster targets not only reduces the average accumulative detection probability P of the underwater targets but also greatly increase the calculation time. Therefore, as the number of targets in the underwater cluster increases, the detection efficiency of the sonar buoy network decreases.

Comparing the deployment scheme with AFWA algorithm in **Fig. 9**, **Fig. 10** and the results of the simulation environment 3 and 4 in **Tab. 1**, it can be seen that when the search region and the number of underwater targets remain unchanged, appropriately reducing the number of fireworks owned by each generation, the number of sparks and Gauss sparks generated by each fireworks will not only slightly increase the average accumulative detection probability P of underwater targets, but also greatly shorten the calculation time. Comparing the deployment scheme with AFWA algorithm in **Fig. 8**, **Fig. 10** and the results of the simulation environment 2 and 4 in **Tab. 1**, it is easier to see the importance of appropriately reducing parameters of the fireworks algorithm.

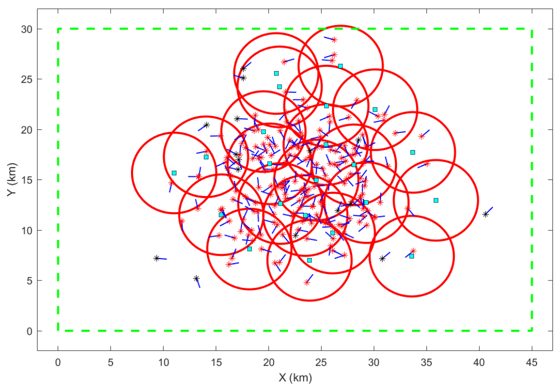
TABLE 1. The main parameter settings and simulation experimental statistical results in the seven simulation environments.

Parameters	The length *l* of the rectangular search region (*km*)	The width *w* of the rectangular search region (*km*)	Number of targets	Minimum empirical value of buoy number	The probability threshold P_0 of underwater targets being detected successfully
environment 1	45	30	80	22	0.8
environment 2	45	30	80	22	0.8
environment 3	45	30	**200**	22	0.8
environment 4	45	30	200	22	0.8
environment 5	45	30	200	**14**	0.5
environment 6	**20**	**16**	200	**6**	**0.8**
environment 7	**40**	**8**	200	6	0.8

Parameters	Number of fireworks owned by each generation	Number of sparks generated by each fireworks	Number of Gaussian sparks generated by each fireworks	The average accumulative detection probability *P* of underwater targets in the five simulation experiments (%)	Average calculation time *t* of buoy deployment in the five simulation experiments (*s*)
environment 1	8	15	12	67.50	35.07
environment 2	8	15	12	90.25	52.09
environment 3	8	15	12	88.00	85.82
environment 4	**5**	**10**	**6**	90.50	38.62
environment 5	5	10	6	80.00	18.01
environment 6	5	10	6	75.50	7.53
environment 7	5	10	6	77.50	7.60

TABLE 2. Statistical results of comparative verification experiments of AFWA, ACO, PSO algorithms in six simulation environments.

Parameters	The average accumulative detection probability *P* of underwater targets in the five simulation experiments (%)			Average calculation time *t* of buoy deployment in the five simulation experiments (*s*)		
	AFWA	ACO	PSO	AFWA	ACO	PSO
environment 1	67.50	41.25	25.00	35.07	41.24	29.43
environment 2	90.25	81.25	70.00	52.09	94.80	62.27
environment 3	88.00	84.00	71.50	85.82	129.47	98.37
environment 4	90.50	--	--	38.62	--	--
environment 5	80.00	70.50	58.00	18.01	28.22	25.11
environment 6	75.50	73.00	45.50	7.53	11.01	6.81
environment 7	77.50	68.00	36.50	7.60	11.49	5.59



(AFWA)

FIGURE 10. Five sets of simulation results corresponding to the simulation environment 4.

Comparing the deployment scheme with AFWA algorithm in **Fig. 10**, **Fig. 11** and the results of the simulation environment 4 and 5 in **Tab. 1**, it can be seen that when the search region and the number of underwater targets remain unchanged, reducing the probability threshold P_0 of underwater targets being detected successfully will reduce the number of sonar buoys which will greatly shorten the calculation time, but it will greatly reduce the average accumulative detection probability *P* of underwater targets at the same time. The same conclusion can be obtained by comparing the deployment scheme with AFWA algorithm in **Fig. 10**, **Fig. 12** and the results of the simulation environment 4 and 6 in **Tab. 1**. Comparing the deployment scheme with AFWA algorithm in **Fig. 12**, **Fig. 13** and the results of the simulation environment 6 and 7 in **Tab. 1**, it can be seen that when the search region of sonar buoys has the same area, but with a different length-width ratio, the average accumulative detection probability *P* of underwater targets and calculation time of the model solving are basically the same. Therefore, the average accumulative detection probability *P* of underwater targets and the calculation time of the model solution are related to the area of the rectangular searching region but have nothing

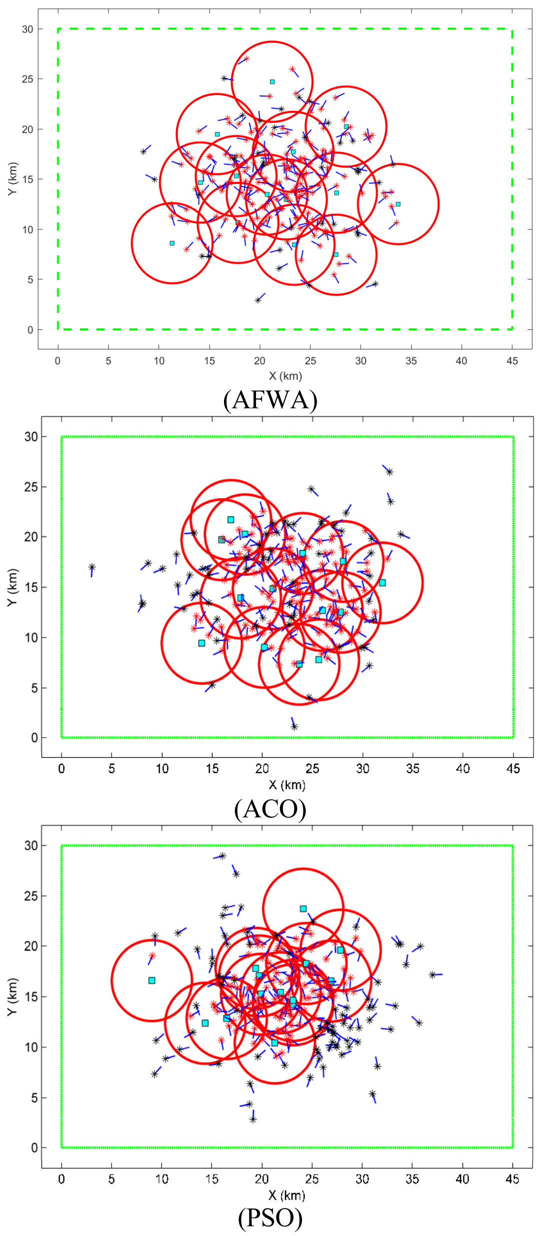


FIGURE 11. Five sets of simulation results corresponding to the simulation environment 5.

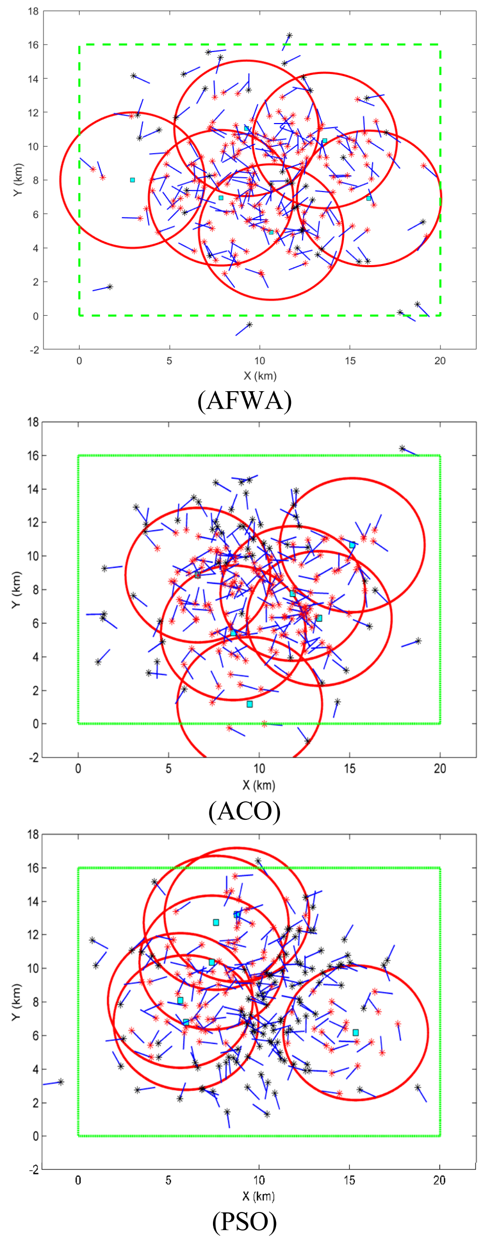


FIGURE 12. Five sets of simulation results corresponding to the simulation environment 6.

to do with the length-width ratio of the rectangular search region.

Comparing the deployment schemes of the three algorithms in **Fig. 7** to **Fig. 13**, it can be seen that under the same environment, the AFWA algorithm is the best, the PSO algorithm is the worst, and the deployment scheme of AFWA algorithm is obviously better than that of the other two algorithms. It can be seen from the results of the deployment scheme that the detection range of buoys under the ACO and PSO algorithms overlap seriously, and the number of buoy detection targets is too small due to the unreasonable placement of buoys, which can not give full play to the detection efficiency. This is because the ACO and PSO algorithms are easy to fall into the local optimal solution. From the comparison results of the simulation experiments in **Tab. 2**, it can be seen that the average cumulative detection probability P of the underwater target under the AFWA algorithm is much higher than that under the ACO and PSO algorithms. From the average time consumption of the buoy deployment simulation calculation, the ACO algorithm takes the longest time and the AFWA and PSO algorithms take the same time, but with the increase of environmental complexity, the AFWA algorithm takes a shorter time than that of the PSO algorithm. The ACO algorithm takes the longest time because of the insufficient information interaction between each individual in the ACO algorithm, while the AFWA algorithm has both good local

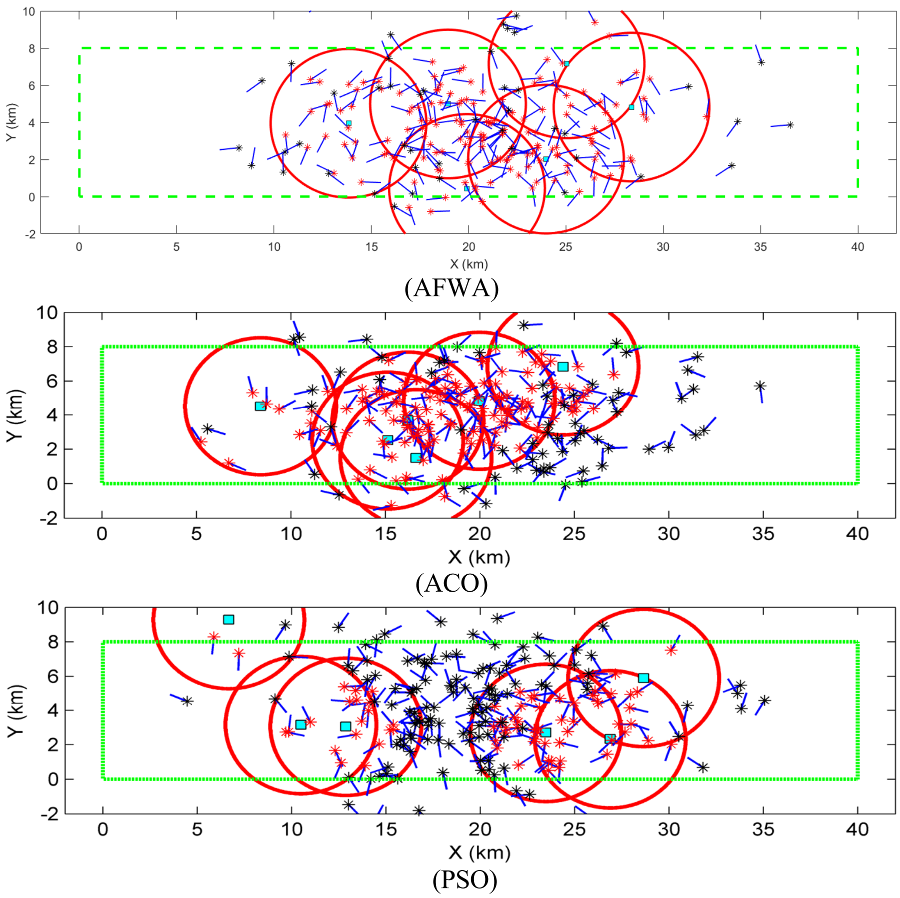


FIGURE 13. Five sets of simulation results corresponding to the simulation environment 7.

search and global search capabilities. The results show that the AFWA algorithm proposed in this paper is effective and superior in solving the problem of sonar buoy deployment. Combining the seven simulation environment experiments, it can be seen that by establishing the mathematical optimization model of sonar buoy deployment under the overview situation of targets being knowing, and applying the adaptive fireworks algorithm to solve the model, we can get a good search efficiency and obtain a sonar buoy deployment scheme close to the actual situation. As long as the appropriate parameters of the fireworks algorithm are selected, a buoy network scheme with high search efficiency can be obtained at a lower computational cost.

V. CONCLUSION AND FUTURE RESEARCH PROSPECT

This paper aims to study the typical problems of deploying sonar buoys in designated sea areas and to study two common problems existing in previous studies. The mathematical optimization model for sonar buoys detection under the overview situation of underwater cluster targets is established, and the adaptive fireworks algorithm is used to solve the optimization problem for obtaining the sonar buoys deployment scheme. The following conclusions can be obtained through simulation experiments:

(1) The distribution law of underwater cluster targets obeyed has a great influence on the sonar buoy network. Under the same experimental simulation environment parameters, the more dispersed the distribution of underwater cluster targets, the lower the average accumulative detection probability P of underwater targets. And the more concentrated the distribution of underwater cluster targets, the higher the average accumulative detection probability P of underwater targets, but the longer the calculation time.

(2) As the number of targets in the underwater cluster increases, the detection efficiency of the sonar buoy network decreases.

(3) The detection efficiency of the sonar buoy network can be greatly improved by appropriately reducing the number of fireworks and offspring sparks in each generation in the adaptive fireworks algorithm.

(4) Reducing the number of sonar buoys will greatly shorten the calculation time, but it will greatly reduce the average accumulative detection probability P of underwater targets at the same time.

(5) The detection efficiency of the sonar buoy network is related to the area of the rectangular searching region but has nothing to do with the length-width ratio of the rectangular search region.

(6) The mathematical optimization model of sonar buoy deployment under the overview situation of targets being knowing and the adaptive fireworks algorithm to solve the model in this paper have a great searching efficiency. As long as the appropriate parameters of the fireworks algorithm are selected, a buoy network scheme with high search efficiency can be obtained at a lower computational cost.

However, the method presented in this paper also shows the following deficiencies, which will be further studied in the follow-up study.

(1) The number of sonar buoys has a great influence on the detection efficiency of underwater targets, but the empirical formula for the number of sonar buoys used in this paper cannot adapt to the changing simulation environment. When the area of the search sea region is similar to that of the circular area of the sonar buoy detection range, the probability of underwater target detection will be greatly reduced. It is necessary to study a method that optimizes the number of sonar buoys simultaneously in future research.

(2) The sonar buoy has a detection blind zone when detecting underwater targets. The follow-up work needs to consider the sonar buoy deployment method when there is a detection blind zone.

(3) The model in this paper is established under the condition of the initial position and course information of underwater cluster targets being knowing. However, in the actual military combat environment, the situation of targets is unknown in more cases. How to establish a sonar buoy deployment model under knowing the general distribution law and distribution range of underwater targets is the content for further research in the follow-up work.

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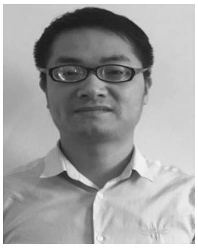

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