

Research on deep-sea submarine position prediction and search and rescue strategy based on multi-intelligence optimization and machine learning

Hanfei Cao*

School of information and communication engineering, Communication University of China,
Beijing, China, 100024

*Corresponding author: Hanfei Cao, caohf9@163.com

Abstract. In this paper, the position prediction and search and rescue strategy of deep-sea submarine are effectively studied by using multi-intelligence optimization and machine learning. First, the possible position of the submarine is predicted by building an accurate position prediction model, combining historical data and real-time ocean dynamic data. Secondly, NSGA-II, a multi-objective optimization algorithm, optimizes the combination of search and rescue equipment carried by search and rescue vessels, determines the best initial deployment point, designs an efficient search mode, and uses Bayesian probability algorithm to evaluate the rescue probability. Through these studies, this paper provides strong technical support for the safe operation and fault rescue of deep-sea submarines.

Keywords: Deep-sea submarines, Position prediction, Multi-objective optimization, CNN, Bayesian probability.

1. Introduction

Although the deep sea has always been a challenging and uncharted territory for humans, with the advancement of technology, we have begun to gradually touch this mysterious deep blue. Maritime Cruises Mini-Submarines (MCMS), a Greece-based company focused on building mini-submarines capable of carrying humans to explore the depths of the ocean. These submarines are designed to deploy independently from the mother ship and sail autonomously to a predetermined area of exploration without tethering. MCMS is currently planning an innovative project to use its advanced submarine technology to provide a unique undersea adventure to the Ionian Sea to visit wreck sites. However, before this project can be implemented, it is necessary to ensure that safety measures meet regulatory requirements. This includes building an accurate position prediction model to monitor the consistency of the submarine's real-time position in the ocean with its intended course, thus ensuring the normal operation of the submarine without trouble. More importantly, in the event of any failure, pre-planned optimal search and rescue strategies must be activated immediately to improve the overall safety of the project.

In order to improve the safety and efficiency of submersible manned deep-sea adventure, this paper mainly focuses on the prediction of submersible position, optimization of search and rescue equipment and formulation of search and rescue strategy.

2. Multi-objective optimization model based on NSGA-II algorithm

2.1. Additional search equipment carried by the main ship and optimization analysis

In the deep-sea submarine search and rescue operation, choosing the right search equipment is crucial, because it directly affects the search efficiency and success rate. The multi-objective linear optimization model is an effective method to evaluate and compare the performance of different search equipment, especially from the three key aspects of cost, search range and accuracy. In order to cope with the possible failure of submersible in the course of the mission and ensure the rapid and effective search and rescue, this paper proposes to carry three key search equipment on the main ship.

The selection of these equipment is based on the latest technological advances in the maritime field and equipment performance analysis, with the aim of maximizing search efficiency and success. The following is a description of the functions of the selected equipment and its application in submersible search:

(1) Multi-beam sonar: Multi-beam sonar can carry out detailed three-dimensional topography of the seabed by transmitting and receiving multiple sound beams

Draw. This device is particularly suitable for accurately mapping large areas of seafloor terrain, including shipwrecks, sea ft or other topographic features.

(2) Laser rangefinder: Laser rangefinder uses a laser beam to measure distance and position, providing high-precision distance measurement results. Although it

Its use under water is limited, but when operating on or near the surface, it can be used to measure distance and speed to a target.

(3) Magnetic detector: magnetic detector can detect the magnetic field changes generated by underwater objects, especially suitable for finding large metal objects

A body, such as a shipwreck or submersible. Such equipment is of particular value for searching in difficult terrain.

Their specific parameters are shown in the following table 1:

Table 1: Device Performance Comparison

Device	Cost (\$/day)	Range(m)	Accuracy (m)
Multibeam Sonar	1987	100	0.5
Laser Rangefinder	485	10	0.01
Magnetic Detector	826	80	2

The introduction of NSGA-II model: Firstly, it is necessary to find the solution set close to the Pareto optimal domain[1-3]. This requires that optimization algorithms not only explore the solution space and find effective solutions, but also that these solutions need to achieve a relatively balanced state in the various target performance[4-7]. The Pareto optimal solution set represents the best tradeoff on all the objectives under consideration, and no one solution is simultaneously superior to the other solutions in the solution set on all the objectives. This solution set provides a range of solutions that a decision maker can choose based on specific circumstances and preference[8]s.

Secondly, it is necessary to generate as diverse a solution set as possible, because a diverse solution set means that the solutions are not only concentrated in a small region of the Pareto frontier, but are widely distributed over the entire efficient frontier[9]. This helps decision makers evaluate the problem from different perspectives and choose the solution that best meets their needs and preferences. In a multi-objective optimization problem, the algorithm should be able to provide solutions that are widely distributed over the entire Pareto optimal frontier to ensure that all possible optimal tradeoffs are covered[10].

Generally speaking, the multi-objective optimization problem is composed of multiple objective functions and some related equations and inequality constraints, which can be described as follows from a mathematical perspective:

$$\min f_1(x_1, x_2, \dots, x_n) \quad (1)$$

$$\min f_r(x_1, x_2, \dots, x_n) \quad (2)$$

$$\max f_{r+1}(x_1, x_2, \dots, x_n) \quad (3)$$

$$\max f_m(x_1, x_2, \dots, x_n) \quad (4)$$

$$s. t. \quad g_i(x) \geq 0, i = 1, 2, \dots, p \quad (5)$$

$$h_j(x) \geq 0, j = 1, 2, \dots, q \quad (6)$$

In the formula, function $f_i(x)$, $\{i = 1, 2, 3, \dots, m\}$ is called the objective function; $g_i(x)$ and $h_i(x)$ are called constraint functions; $x = \{x_1, x_2, \dots, x_n\}^T$

It's an n -dimensional design variable. $X = \{x | x \in R^n, g_i(x) \geq 0, h_j(x) = 0, i = 1, 2, \dots, p, j = 1, 2, \dots, q\}$ is called the can of the above formula Row field.

In this multi-objective optimization problem, there are m ($m \geq 2$) objective functions (r minimizing objective functions, $m - r$ maximizing objective functions)

Number) and $(p + q)$, $p, q \geq 0$ constraint functions (where there are p inequality constraints and q equality constraints).

The establishment of NSGA-II model: In this model, in order to fully consider the equipment requirements of rescue ships when performing deep-sea submarine rescue missions, this paper introduces a multi-objective optimization framework, aiming at balancing three key indicators: cost, detection range and detection accuracy. The devices include multi-beam sonar, laser rangefinders and magnetic detectors, the number of which is expressed by the variable x_i ($i = 1, 2, 3$), respectively. For each device, its purchase price and

The maintenance cost per unit time is expressed by P_{ui} and P_{mi} respectively. Based on these parameters, we define the total cost function W_{max} and total probe

Girth LR and total accuracy AP are as follows:

$$W = \sum_{i=1}^3 x_i P_{ui} + \sum_{i=1}^3 x_i \int_0^t P_{mi} dt \quad (7)$$

If the detection ranges of the three are L_i respectively, the total detection range is LR (x) :

$$L_R = \sum_{i=1}^3 x_i L_i \quad (8)$$

Suppose the detection accuracy of the three is A_i respectively, then the total accuracy is AP (x) :

$$A_p = \sum_{i=1}^3 x_i A_i \quad (9)$$

In the process of building the model, objective functions and constraints are set to minimize the total cost W , minimize the total accuracy loss A_p , maximize the total detection range LR, and satisfy the cost upper limit W_{max} and the minimum detection range L_{min} . $x = \{x_1, x_2, x_3\}^T$ are three-dimensional design vectors. Let S be a feasible domain for multi-objective optimization, and $f(X)$ be a vector objective function for multi-objective optimization. If $f(X) \leq f(X^-) \forall X \in S$, then X^- is said to be a non-inferior solution of the multi-objective optimization problem, i.e. a non-dominated solution. Multi-objective optimization problems generally have multiple non-inferior solutions, and the set of all the non-inferior solutions is called the non-inferior set. The objective function corresponding to all the non-inferior solutions forms the non-inferior optimal objective domain of the multi-objective optimization problem and also becomes the Pareto Front.

The analysis shows that the objective functions and constraints of multi-objective optimization are as follows:

$$\min W(x_1, x_2, x_3) \quad (10)$$

$$\min A_p(x_1, x_2, x_3) \quad (11)$$

$$\max L_R(x_1, x_2, x_3) \quad (12)$$

$$s. t. \quad W(x_i) \leq W_{max} \quad (13)$$

$$L_R(x_i) \geq L_{min} \quad (14)$$

$$A_p(x_i) \leq L \quad (15)$$

$x = \{x_1, x_2, x_3\}^T$ is a three-dimensional design vector. Let S be a feasible domain for multi-objective optimization, and $f(a)$ a vector objective function for multi-objective optimization. If X^- is the non-inferior Solution of the multi-objective optimization problem, that is, the Non-dominated solution. There is generally more than one Non-inferior solution for multi-objective optimization

problems, and the Set composed of all non-inferior solutions is called non-inferior set. All the objective functions corresponding to the non-inferior solutions form the non-inferior optimal objective domain of the multi-objective optimization problem, which is also called the ParetoFront(Figure 1).

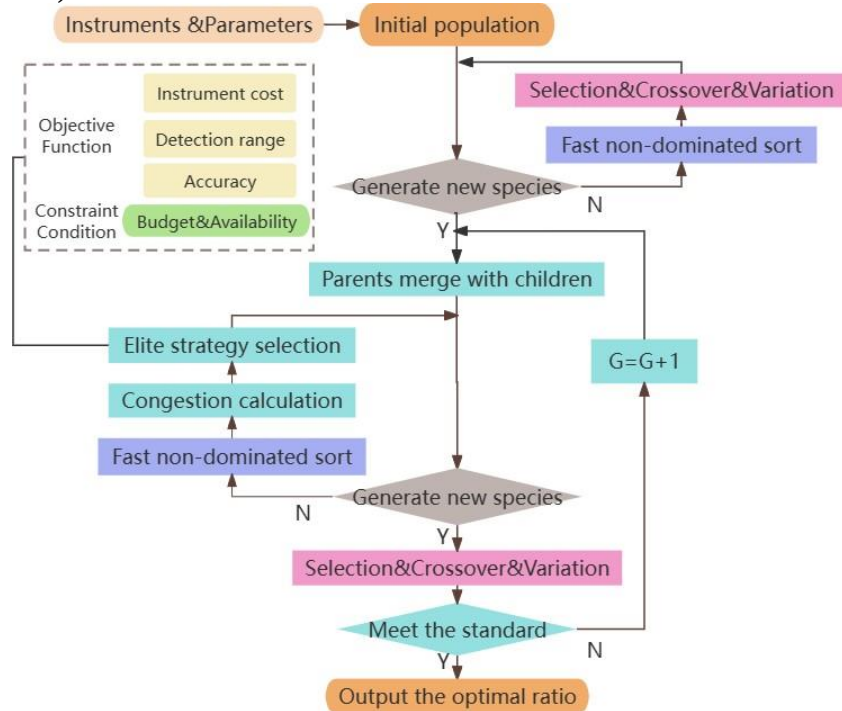


Figure 1. NSGA-II algorithm solves flowcharts

To solve the problem, we first randomly generate a value for each decision variable according to the constraints: budget and the equivalent length of the submarine, constitute an individual, generate the initial population, and then calculate the objective function value $f_i(x)$ for each individual and the constraint condition value $g_j(x)$ to evaluate the population fitness. According to the NSGA-II algorithm, the individuals are non-dominated sorted, each individual is assigned a grade r , and the number of n_p that each individual is dominated is marked. Initialization is performed first, setting the number of initially dominated ($n_p=0$) for each individual and the domination set to empty. According to the non-dominant relationship:

$$x_p < x_q \Leftrightarrow \forall i, f_i(x_p) \leq f_i(x_q) \wedge \exists j, f_j(x_p) < f_j(x_q) \quad (16)$$

Each pair of individuals p and q is compared, and the situation of p being dominated by q is counted. Meanwhile, the domination set of q and the number of p being dominated are updated, and the individuals of the same rank are placed together according to the number of n_p being dominated. For each individual q in the dominant set of individual p , the updated number of individuals dominated ($n_q = n_q + 1$). The operation is repeated until all individuals are assigned to a certain level, resulting in a series of levels, each containing a set of individuals that are not dominated by other individuals. Such a hierarchy constitutes the Pareto frontier.

Next, determine the degree of crowding according to the non-dominated order, and rank the individuals of each rank according to the dominated one

The number n_p is sorted in ascending order. According to the formula:

$$d_p = \sum_{i=1}^m \frac{|f_i(x_{p-1}) - f_i(x_{p+1})|}{f_{max_i} - f_{min_i}} \quad (17)$$

For individuals of the same rank, calculate the crowding distance for each individual.

Then a selection operation is carried out. After fast non-dominated sorting and calculation of crowding distance, a selection operation is carried out to select parent individuals to generate a new population. Because of the ranking and crowding calculation, each individual i in the population gets

two attributes: non-dominant order i (rank) and crowding id. The partial order relation is defined when the condition $i(\text{rank}) < id$ is met, or $i(\text{rank}) = id$ and $id > jd$ is met. That is to say: if the non-dominant ordering of two individuals is different, take the individual with the smaller ordering number (the individual separated first in hierarchical sorting); If two individuals are in the same level, take the less crowded individual around.

Finally, crossover and mutation operations are carried out and then repeated selection, crossover and mutation operations are carried out on the basis of existing solutions according to the convergence of the algorithm. Crossover operations are performed to increase population diversity, avoid local optimal solutions, mutation operations are performed to introduce new individuals, increase the breadth of the search space, and output a set of individuals that represent multiple excellent solutions to the problem until convergence conditions are met.

For practical application problems, the company only needs to change its constraints according to its own planning situation, then the corresponding number of devices can be calculated. By analyzing the financial expenditure reports and equipment expenditure of internationally renowned maritime shipping companies, this paper puts the specific values of the cost, detection range and resolution of the three kinds of equipment into the NSGA-II model, considers shortening the search and rescue time as the first goal, reducing the overall cost as the second goal, and introduces the weights of 74% and 26% as parameters. According to the model calculation and solution, the optimal equipment allocation should be invested in 5 multi-beam sonars, 11 laser rangefinders and 16 magnetic detectors, which can ensure the minimum cost in the shortest search and rescue time. The three-dimensional relationship between the number of three devices and the constraints is shown in the figure 2 above.

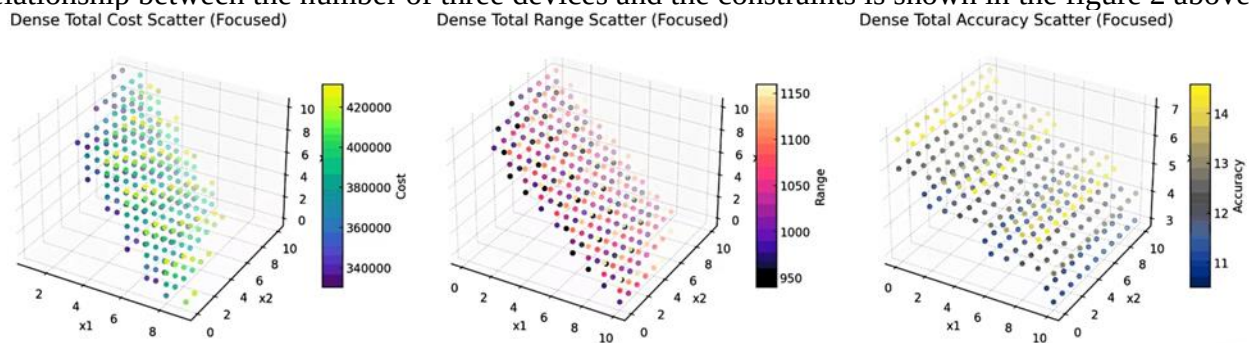


Figure 2. Optimize the results of 3D scatter plots

2.2. Additional equipment carried by the rescue vessel

In order to improve the efficiency of the rescue and ensure that the submarine can be quickly located after failure, the additional equipment carried on the rescue ship must be able to pick up the signal emitted by the submersible's black box. Therefore, this paper believes that rescue ships should carry an additional Underwater acoustic positioning device (ULB receiver), which is used to receive Underwater Locator Beacon (ULB) signal receiver, and is one of the most critical equipment of search and rescue submersibles. When a submersible malfunctions, its black box automatically releases acoustic signals. The underwater acoustic positioning device can receive these signals and determine the position of the submersible by analyzing the arrival time and strength of the signals.

3. Neural network prediction model

3.1. Initial Deployment Point

A prediction model based on neural network is proposed to solve the location problem of submarine after failure. Since the submersible needs to send information to the main ship regularly to report its position and environment, considering that the most likely factor for the failure of the submersible is the loss of power of the hull and the loss of communication with the main ship, the worst possible situation is analyzed, that is, the submersible has power and communication at the

same time. At this time, the position model of the submersible can be regarded as the case that only the noise model is retained. At the same time, due to the influence of internal and external environmental factors, the main influencing factor for the position movement of unpowered submersible is ocean current, so only the influence of ocean current in the sea area is considered(Figure 3).

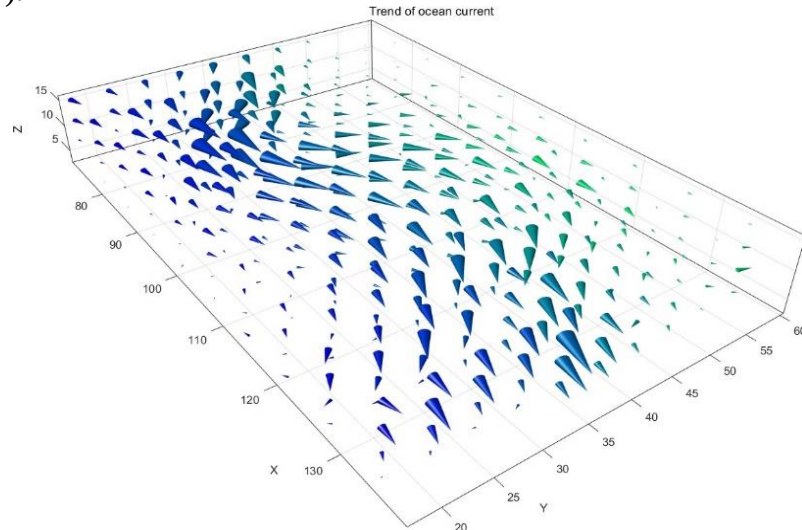


Figure 3. The speed and direction of currents in the local sea

In order to shorten the locating time of the missing submersible to the maximum extent, the choice of the initial deployment point of the rescue ship is particularly critical. Due to the constant speed of the rescue vessel, it is an effective strategy to select the point with the shortest distance from the lost submersible as the best initial deployment point. Since the rescue operation is carried out from the surface, the surface point directly above the most likely location of the missing submersible is naturally the best initial deployment point for the rescue vessel. The determination of this depends on accurate prediction of the most likely drift direction of the lost vehicle, as well as the drift distance calculated based on the last status information. In order to achieve the above goals, this paper adopts the convolutional neural network model to predict the drifting direction of the lost submersible, and estimates the possible drifting distance of the submersible by using the final state information sent by the submersible before the loss of contact, such as the speed and direction of the ocean current. Combined with these two key pieces of information, the optimal initial deployment point for rescue vessels can be pinpointed, ensuring that rescue operations can be carried out quickly and effectively.

First of all, the drift distance is predicted: combining the speed and time of the ocean current, the drift distance can be calculated. Drift distance D can be used with the following public Formula estimation:

$$D = V \times T \quad (21)$$

V is the velocity of the last transmitted current before contact was lost, and T is the time of loss.

Then predict the direction:

The basis of model construction: (1) Reference point setting: the geographical coordinates of the last communication between the submersible and the main ship are used as reference points

The predicted position will be performed relative to this point.

(2) Direction consideration: in the horizontal direction, it is subdivided into east, South, west, north and four diagonal directions (southeast, southwest, northeast and west, North) to assess the relative probability of a submersible appearing in these directions.

Establishment of Convolutional Neural Network (CNN): In order to predict the possible position of submersible that lost power and communication with the main ship under the influence of ocean currents, a prediction model based on convolutional neural network (CNN) is proposed in this paper. The construction of the model starts with the collection of training data, the collection of ocean current changes in the local sea area as the input feature, and the movement orientation of floating objects in

the corresponding sea area as the output target, and the construction of a multidimensional dataset. The data set is reasonably divided into training set and validation set to ensure the effectiveness and generalization ability of model training(Figure 4).

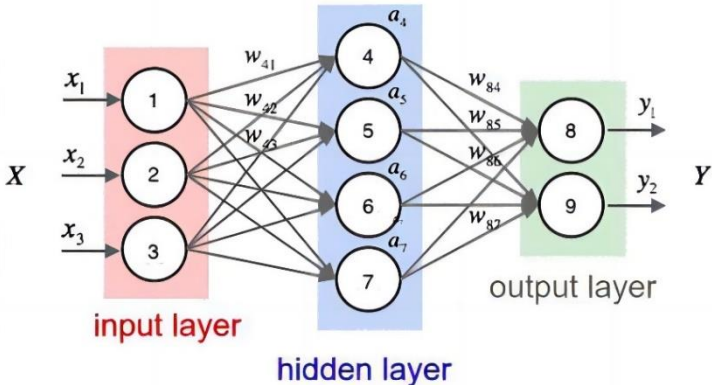


Figure 4. Schematic diagram of CNN

In the input layer, the ocean current data is processed into a suitable matrix format to ensure that the column and row condition of the convolutional neural network input is satisfied. Then, several different convolution kernels are selected in the convolution layer to capture the key features of the dataset. By selecting the appropriate sliding window size, the convolution kernel slides on the data set and performs the product and operation of elements to get the feature map. This process enhances the ability of the network to capture data features. Subsequently, the nonlinear activation function ReLU is applied to introduce the necessary nonlinearities to the model, allowing the model to learn more complex data representations.

Pooling layer selects the most significant feature from the feature map through the maximum pooling operation, reduces the size of the feature map, reduces the computational complexity, and improves the adaptability of the model to input changes. In the output layer, eight neurons were set in the model, corresponding to the probability distribution in eight directions. Softmax function was used as the activation function to convert the output value into the probability distribution, so as to predict the possible orientation of the submersible.

In order to quantify the difference between the predicted label distribution and the actual label distribution, the model uses a cross-entropy loss function. At the same time, Adam optimizer was selected for parameter optimization, and the learning rate was set to $1e-4$, in order to achieve fast and stable training effect. During the training process, the performance of the model on the verification set is continuously monitored for necessary hyperparameter tuning, and an early stop strategy is adopted to prevent overfitting. The training will be stopped when the verification set performance does not improve significantly in successive training cycles(Figure 5).

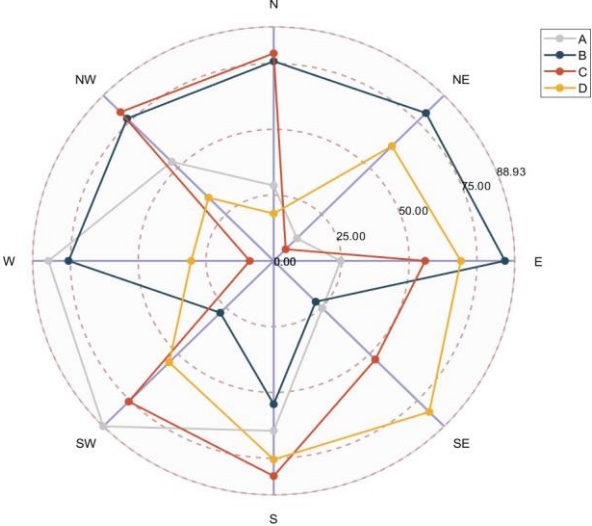


Figure 5. Direction prediction radar map

Finally, the probability of eight directions is predicted, the highest probability direction is selected, and the best deployment point can be determined by combining the drifting distance. This paper assumes that the coordinates where the submersible last communicated were $36^{\circ}34'$ north latitude, $21^{\circ}8'$ east longitude, and about 240 meters below the sea level. The data of this sea area are input into the convolutional neural network model, and the possible prediction probabilities of the output eight directions are as follows: Due East is 35% likely, due south is 10% likely, due West is 3% likely, due North is 8% likely, Southeast is 15% likely, southwest is 4% likely, northeast is 9% likely, northwest is 16% likely. Considering the communication time interval and ocean current data, the optimal initial deployment point is estimated to be at sea level at $36^{\circ}12'$ N and $21^{\circ}45'$ E.

3.2. Search Mode

During the search for the missing submersible, if the distress call device carried by the submersible is able to send a distress signal in one direction to the outside world in case of power system and communication system failure, additional equipment carried on the rescue ship can receive this signal. The strength of the signal decreases with the increase of the distance from the receiving device, and it may be affected by the noise signal generated by multiple sources of interference in the sea. Nevertheless, the power of the submersible signal is much greater than the natural noise, which provides the basis for the detection and positioning of the signal.

Based on the above analysis, this study proposed a gradient descent algorithm based on neural network model as the optimal search mode to find the location with the greatest signal intensity, that is, the most likely location of the submersible. The deployment point predicted by the neural network model is used as the initial position of the detector, and the gradient of the signal strength is simulated by measuring the signal strength at several points near the current position of the detector. This process involves moving the detector a small step long along the basic directions of north, south, east and west to determine which direction increases the signal strength most significantly. Subsequently, the position of the detector is constantly updated according to this estimated gradient direction, following the steps of updating parameters along the negative gradient direction in the gradient descent algorithm, until the increase in signal strength is below a certain threshold or the number of detector moves reaches the upper limit, which indicates that the detector may be close to the target source (Figure 6).

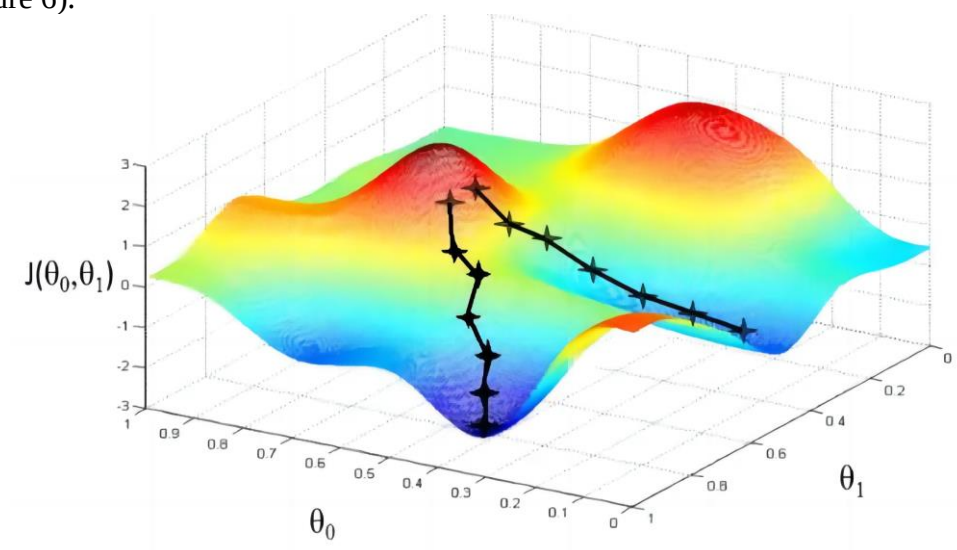


Figure 6. Schematic diagram of the gradient descent algorithm

The key of this method is the reasonable choice of moving step size to ensure that the detector can effectively approach the target source rather than skip it, and also ensure the efficiency of the search process. Eventually, when the probe stops moving, more refined means can be taken to further locate the precise position of the submersible, such as subtle adjustments in a smaller area or cross-verification of positioning using other assistive technologies.

3.3. Probability function of finding submersible

In order to accurately determine the location of the lost submersible and estimate the search probability, this paper considers that the submarine after losing contact is located at the neutral buoyancy point and drifting in the horizontal direction only under the influence of ocean currents. The search probability is affected by the combined influence of the drifting distance over time, the attenuation of the signal sent back by the submersible and the accumulated search results obtained by the gradient descent method. Based on Bayesian probability law, the function relationship of search probability with respect to time and cumulative search results is established.

The search for the missing submersible involves many uncertainties, including the exact location of the submersible, the direction of drift, and the attenuation of signal strength. At the start of the search, information about the location of the submersible is likely to be incomplete or based on partial observation data. Bayes' theorem can guide the search more precisely by combining prior knowledge (such as ocean current data, previous experience of similar events) with new observational data (such as signal strength, cumulative search results), enabling it to update estimates of the submersible's position in an environment of uncertainty and incomplete information.

In addition, Bayes' theorem allows us to dynamically update probability estimates of submersible positions using new information generated during the search.

The ability to effectively integrate information from different sources, both quantitative and qualitative, provides a unified framework for assessing possible positions of submersibles.

To sum up, this paper uses Bayesian probability evaluation algorithm to solve the function of probability and time and cumulative search results. First of all, we assume that the submersible is only affected by the ocean current in the horizontal direction after losing contact and drifts in the horizontal direction, and its position change can be described by the following differential equation:

$$\frac{dX(t)}{dt} = v_{current} \quad (18)$$

Where $x(t)$ represents the position of the submersible at time t , $v_{current}$ represents the horizontal speed of the ocean current, and the specific value is different in the specific sea area.

The possible position of the submersible should be predicted based on historical data and real-time ocean dynamic data. Through analysis and verification of a large number of data, it is known that the drift radius of the submersible is positively correlated with time, and the probability $P(t)$ is positively correlated with the reciprocal of the square of the drift radius, expressed as:

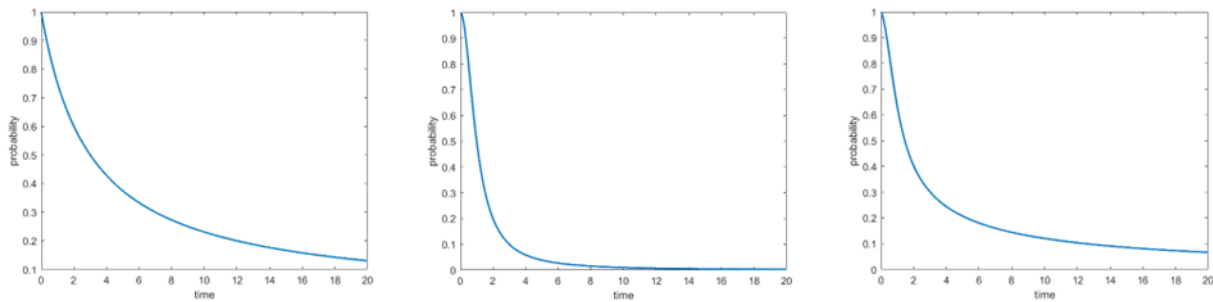
$$P(t) = \frac{C}{(kt)^2} \quad (19)$$

Where k is the drift rate and C is a constant. Because this article assumes that the underwater locator beacon is carried on the submersible, after the loss of contact, the rescue ship receives

The signal strength of the underwater positioning beacon decays with time, which can be expressed as:

$$S(t) = S_0 e^{-\lambda t} \quad (20)$$

Denotes, where S_0 is the initial signal strength, ρ is the attenuation constant, and t is the time. Signal attenuation will indirectly affect the scope and accuracy of search and rescue, and it is necessary to update the signal intensity model in real time to guide the search. Therefore, with the passage of time, the drifting distance of the submersible will continue to increase, and the circular search range will also increase, and the finding probability is inversely proportional to the search range, which is proportional to the square of the radius, and the radius is proportional to the drifting time, so the finding probability is inversely proportional to the reciprocal of the square of time. Moreover, considering the attenuation of the signal strength of the underwater positioning beacon over time, Finally, the two influencing factors are weighted to obtain the function graph of finding probability change over time (Figure 7):



(a) The positioning signal decays over time (b) The probability of finding is the relationship between the square of the drift time with time (c) The probability of finding is the relationship between the square of the drift time with time

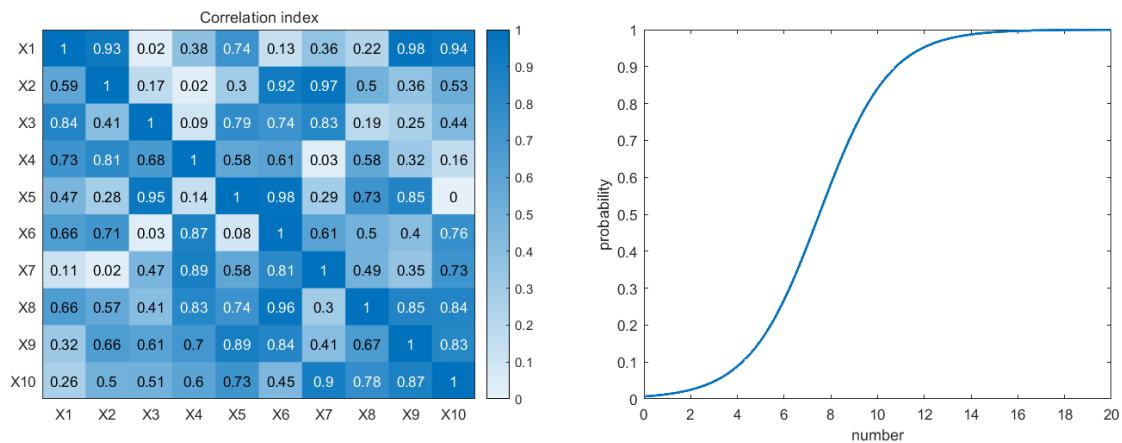
Figure 7. The impact of time

In the search process, we use gradient descent method to dynamically adjust the search direction, always searching in the direction of the maximum signal intensity gradient, in order to minimize the positioning time. After each search, the excluded extreme values (interfering objects) update the probability distribution of the search area, which in turn affects the subsequent search strategy.

Bayes' theorem provides a way to calculate the probability of one event occurring if one event is known to occur. In this model, by comprehensively considering factors such as previous search experience, possible drifting path of submersible and ocean current data, we determined the existing possible probabilities through CNN convolutional neural network, quantified all possible hypotheses with the help of attenuation trend of observed signal strength and cumulative search results, and adopted Bayesian probability formula:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \quad (21)$$

Update posterior probability $P(H | E)$, that is, the update probability that the submersible is located in a specific location. The prior probability is based on the drift model and historical data to define the prior probability distribution of the possible position of the submersible. Likelihood function $P(H | E)$: Based on the signal attenuation model and the received signal strength, calculate the probability that the current signal is observed at a given submersible position, i.e. $P(E | H)$. Posterior probability update: The posterior probability $P(H | E)$ of submersible position is updated by using Bayes' theorem, and the search strategy is continuously optimized in combination with the cumulative search results, that is, when one interference source is excluded, the influence of other interference sources changes, and the function graph of finding probability and cumulative search results is finally obtained through the correlation coefficient between interference sources(Figure 8).



(a)Correlation coefficient plot between interferers (b) The relationship between the probability found and the cumulative search results

Figure 8. The impact of cumulative search results

From the above analysis, it can be seen that the rescue probability is related to both the search range and signal strength. Therefore, with the increase of time, the search scope will gradually increase, and the signal strength will decay with time, so the rescue probability will show a downward trend, and the decline amplitude will gradually decrease until it reaches the probability 0. With the increase of cumulative search and rescue results, the rescue probability shows a rising trend, but at the same time, with the passage of time, the search scope will also increase, so the increase first increases and then decreases, and finally tends to probability 1.

4. Conclusions

In this paper, multi-intelligence optimization and machine learning techniques are used to effectively solve the problem of deep-sea submarine position prediction and search and rescue strategy. By establishing accurate position prediction model, optimizing the combination of search and rescue equipment, determining the best initial deployment point, designing efficient search mode, and evaluating the rescue probability, it provides important technical support for the safe operation and fault rescue of deep-sea submarines. This provides an important reference for the development of deep-sea submarine technology and seabed resource exploration in China.

References

- [1] Mi S, Liu J, Cai L, et al. Multi-objective optimization of two-phase ice slurry flow and heat transfer characteristics in helically coiled tubes with RSM and NSGA-II [J]. *International Journal of Thermal Sciences*, 2024, 199108942.
- [2] Li M, Ma H, Lv S, et al. Enhanced NSGA-II-based feature selection method for high-dimensional classification [J]. *Information Sciences*, 2024, 663120269.
- [3] Kazemnadi Y, Nazari M, Kerachian R. Adaptive reservoir operation considering water quantity and quality objectives: Application of parallel cellular automata and sub-seasonal streamflow forecasts [J]. *Journal of Environmental Management*, 2024, 354120294.
- [4] Zuo W, Li F, Li Q, et al. Multi-objective optimization of micro planar combustor with tube outlet by RSM and NSGA-II for thermophotovoltaic applications [J]. *Energy*, 2024, 291130396.
- [5] Zeid A, Yahmedi A A, Zaier R, et al. Multi-objective design optimization of an in-pipe inspection robot[J]. *Franklin Open*, 2024, 6100071.
- [6] Ke E, Zhao J, Zhao Y, et al. Coupled and collaborative optimization model of impervious surfaces and drainage systems from the flooding mitigation perspective for urban renewal [J]. *Science of the Total Environment*, 2024, 917170202.
- [7] Sigue S, Abderafi S, Bounahmidi T. Multi-objective optimization of a forward osmosis process for desalination using a non-dominated sorting genetic algorithm [J]. *Journal of Water Process Engineering*, 2024, 58104804.
- [8] Zhu F, Liu Y, Lu C, et al. Research on thermal energy management for PHEV based on NSGA-II optimization algorithm [J]. *Case Studies in Thermal Engineering*, 2024, 54104046.
- [9] Zhang Z, Guo Y, Tao Q. Dynamic multi-objective path-order planning research in nuclear power plant decommissioning based on NSGA-II [J]. *Annals of Nuclear Energy*, 2024, 199110369.
- [10] Qu Y, Song B, Cai S, et al. Study on the Optimization of Wujiang's Water Resources by Combining the Quota Method and NSGA-II Algorithm [J]. *Water*, 2024, 16(2).