A Comprehensive Study of Data Fusion-Based Search and Path Planning for Submersibles

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Abstract. With the increase in deep-sea exploration activities, the safety challenges faced by submersibles in complex marine environments have highlighted the importance and urgent need for search and rescue efforts. It is important to protect the marine environment and maintain the safety of personnel while minimizing economic losses. In this study, this paper predicted the wreck paths of submersibles by considering factors such as ocean currents, topography, and energy loss to obtain the wreck paths under different wreck scenarios. The rescue path of AUV equipment to the wrecked submersible is simulated using a genetic algorithm, which ensures that the search and rescue of the wrecked submersible is completed in a short period.

Keywords: Underwater search and rescue, Logistic, Genetic algorithm, Circular search, QGIS.

1. Introduction

The importance of the oceans and seas in today's world is unquestionable, whether in the fields of economics, military, or scientific research [1, 2]. With the deepening of human exploration of the deep sea and the increase in utilization activities, submersibles have become the main tool for exploration of the ocean depths [3, 4]. However, the complexity and unpredictability of the deep-sea environment pose great challenges to the safe operation of submersibles. Therefore, the search and rescue (SAR) of submersibles is of particular importance [5], The safety of submersibles and their crews is at stake and also affects the sustainability of marine scientific research and deep-sea resource development. In recent years, there have been several lost submersible incidents around the world, which not only expose the weakness of submersible technology and operation management but also highlight the urgent need to strengthen the rescue capability of the emergency response mechanism of submersibles. Therefore, this study focuses on underwater localization and prediction of lost submersibles and rescue path planning to effectively respond to their emergencies in complex marine environments.

To solve the problem of localization of a submersible in a wrecked state, the team built a regression model based on logistic regression, which can be applied to emergency response, disease risk prediction, psychological analysis, and so on [6-8]. For the path prediction of search and rescue apparatus in the process of submersible search and rescue, this paper have established a search and rescue model based on a genetic algorithm. The genetic algorithm is the most researched and widely used mainstream algorithm in robot path planning mostly applied in the field of navigation and exploration [9], The team seeks the shortest path problem of the search accordingly. To ensure the coverage of the search, the genetic algorithm is supplemented with a roulette wheel method, a selection strategy based on fitness scaling, to keep the number of individuals in the population constant [10]. Round search has also been added, which improves search performance by extending the search time.

Firstly, the wrecked submersible is divided into two states: lost and disabled and only lost, and consider the influencing factors on the trajectory of the submersible under the two states, and use the logistic regression model to synthesize and analyze the influencing factors, and finally derive the trajectory of the wrecked submersible. Then search path is modeled by a genetic algorithm, and a circular search is added to ensure the accuracy and speed of the search.

2. Submersible Search and Rescue Operation Analysis

The variability of the ocean environment and the uncertainty of the dynamics of a lost submersible is one of the key challenges in the study of submersible search and rescue operations. To more accurately predict the motion trajectory of a lost submersible, the team conducted a detailed analysis of the seawater density, ocean currents, seafloor topography, and submersible dynamics in the study area.

2.1. Analysis of Seawater Density

When a submersible is lost, it is not possible to directly observe the density of seawater through the equipment carried by the submersible, thus making it impossible to calculate changes in seawater buoyancy in real-time. This situation makes it more difficult to analyze the force on the submersible and predict its trajectory. However, the change in seawater density has a certain regularity and usually changes with the increase in depth. Generally speaking, the density of seawater is low in the surface layer and gradually increases with depth until it reaches a certain saturation value, and then the density tends to stabilize. Given this, to speculate the density of seawater at different depths, the team adopted an improved form of the logistic function to establish a predictive relationship between seawater density and seawater depth:

$$\rho(h) = \rho_0 + \frac{(L-\rho_0)}{1+e^{-K(h-h_0)}} \tag{1}$$

Where h represents the current submersible dive depth, L represents the saturation density of seawater, h_0 with increasing dive depth indicates the depth at which the seawater density increases significantly, K represents the rate of change of seawater density, and ρ_0 represents the density of seawater at the sea surface.

For analysis, it is assumed that the initial submersible depth is -3500m, the saturated density of seawater is 1030 kg/m3, the depth of significant density increase is -300m and the rate of change is 0.03. It can be seen from Eq. (1) that the density of seawater at the seabed is mainly affected by the density of seawater at the sea surface. Therefore, the density of sea surface seawater at the place where the submersible is lost is taken as the benchmark value ρ_0, which is used to calculate the change of seawater density during the whole process. Through the simulation calculation, the relationship of seawater density change with depth (the negative number of the horizontal coordinate represents the depth under the sea) is derived, as shown in Figure 1.

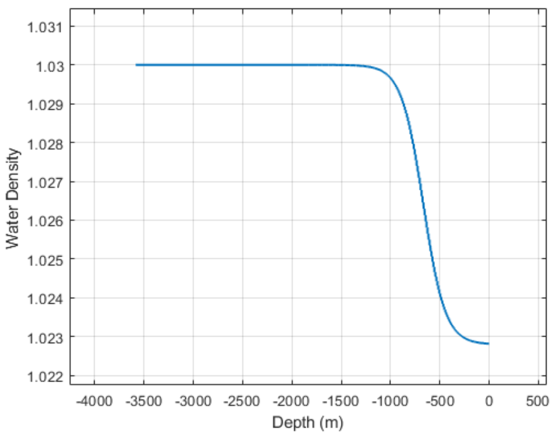

Figure 1. Density variation curve of seawater

Calculate the magnitude of the buoyant force on the submersible by using the following equation:

$$F = \rho(h) \cdot g \cdot V \tag{2}$$

Where g is the gravitational acceleration and V is the volume of the submersible.

To obtain more accurate analysis results, after several parameter adjustments and optimizations, the g was finally set at 9.80m/s2 and the V was set at 154.58m3.

The seawater surface density data were obtained from the Copernicus Marine Service website (https://marine.copernicus.eu/) and contour plots of seawater surface density were produced using QGIS software and visualized as in Figure 2.

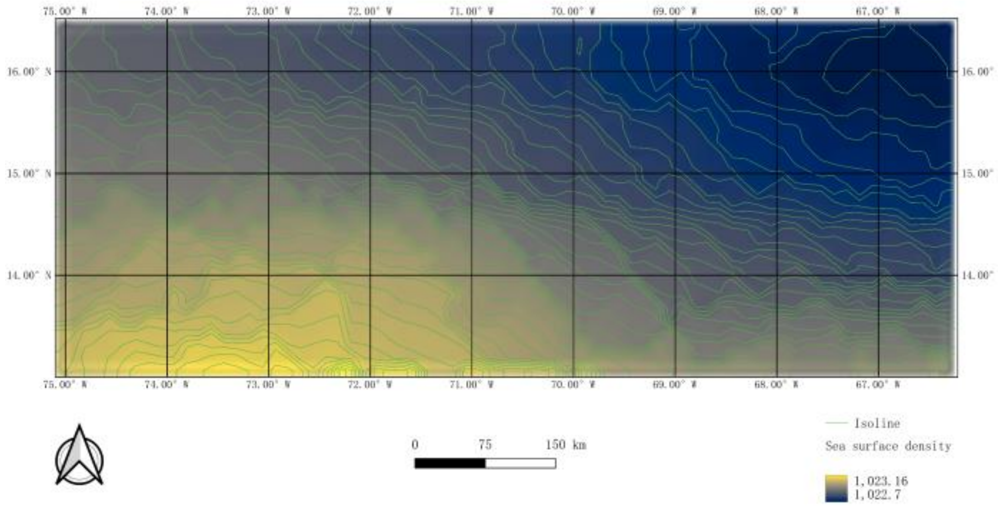

Figure 2. Seawater surface density contour plots

2.2. Analysis of Ocean Current

Currents are large-scale movements of water in the ocean that can have a significant effect on the trajectory of a submersible after a wreck. The speed and direction of currents vary with depth, latitude, and longitude. When a submersible is wrecked, its power system may be disabled or damaged, at which point ocean currents become a major factor in the movement of the submersible. Currents can carry a submersible away from the wreck site, allowing it to drift into an area away from search and rescue personnel. The speed and direction of the currents can also affect the difficulty of search and rescue by the submersible, and current analysis is an integral part of submersible search and rescue operations.

Current data for the study area was obtained from the Current Data website (http://earth.nullschool.net). To facilitate data collection, the team divided the study area into 360 blocks and recorded the latitude and longitude coordinates of each block. Based on these coordinates, the current data corresponding to the coordinates were collected, and the current magnitude isosurface maps of the study area were plotted by Surfer in using kriging interpolation to obtain current data for the study area, as shown in Figure 3.

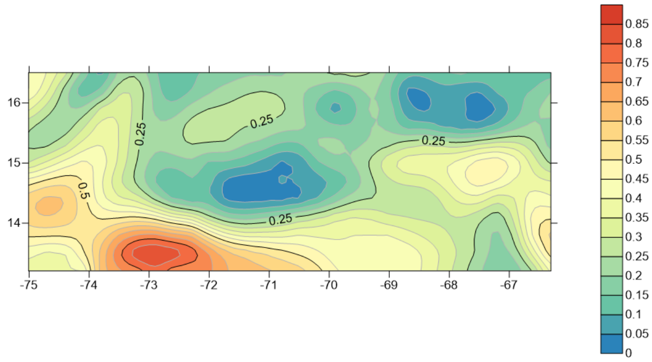

Figure 3. Isosurface map of ocean currents

To improve the spatial resolution of the data for better prediction accuracy, the collected data were resampled using a bilinear interpolation algorithm. Bilinear interpolation is a method commonly used to interpolate two-dimensional gridded data. It is suitable for linear interpolation on four known points for the values of any point in two dimensions [11]. The principle is as follows:

Suppose the four known points are: (x_1, y_1), (x_2, y_1), (x_1, y_2), (x_2, y_2), and the corresponding function values are f_{11}, f_{21}, f_{12}, f_{22}. The mathematical formula for bilinear interpolation can be expressed as:

$$f(x,y) = \frac{(x_2-x)(y_2-y)}{(x_2-x_1)(y_2-y_1)} f_{11} + \frac{(x-x_1)(y_2-y)}{(x_2-x_1)(y_2-y_1)} f_{21} + \frac{(x_2-x)(y-y_1)}{(x_2-x_1)(y_2-y_1)} f_{12} + \frac{(x-x_1)(y-y_1)}{(x_2-x_1)(y_2-y_1)} f_{22} \tag{3}$$

Where $f(x, y)$ is the interpolation result.

2.3. Analysis of Seafloor Topography

The topography of the seabed has a significant impact on the trajectory of a wrecked submersible and search and rescue operations. Complex seafloor topography may cause the submersible to become trapped, damaged, or drift into areas that are difficult to search, thus increasing the difficulty and decreasing the success rate of search and rescue. Detailed analysis of the seafloor topography of the target area is required before developing and executing SAR operations.

The team obtained high-precision digital elevation model (DEM) data of the target area through the Global Multi-Resolution Terrain website(https://www.gmrt.org/). Subsequently, QGIS software was used to visualize the acquired DEM data in three dimensions, as shown in Figure 4, to visualize the characteristics of the seabed topography and to provide a basis for the analysis of the subsequent search and rescue operations.

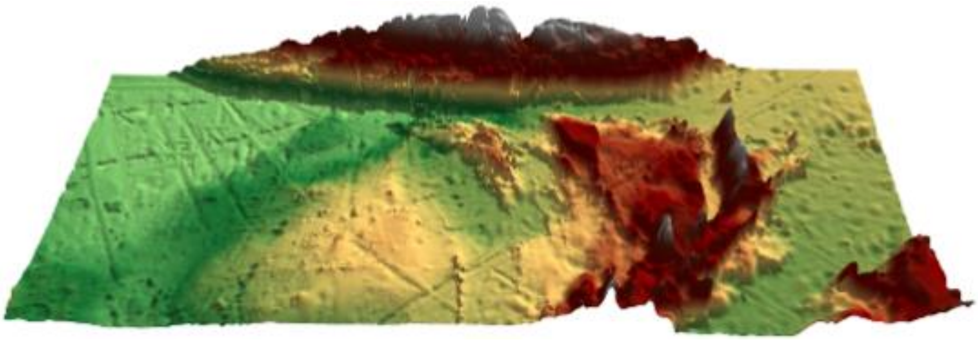

Figure 4. 3D display of seafloor topography

2.4. Analysis of Submersible Power

The power system of a submersible has a decisive influence on its trajectory after a crash. Once the power system fails or is damaged, the submersible will be out of control and subject to the influence of ocean currents and seafloor topography and drift passively.

To improve the prediction accuracy, the prediction step is set to 1 second in this study to obtain a higher time resolution. Meanwhile, the state of the wrecked submersible is divided into two main categories: lost and disabled and only lost.

(1) Lost and disabled: The power system and communication system of the submersible have been disabled, and the submersible is unable to control the navigation and contact with the outside world independently. The submersible will be affected by ocean currents, seabed topography, buoyancy energy loss, and other factors and drift passively. In this case, it is assumed that the speed of the submersible is v, and it will be subject to the influence of the marine environment, which is mainly manifested in the following aspects:

Effect of energy loss. A submersible moving in seawater loses its kinetic energy due to the resistance of seawater. To simulate the energy loss, the loss factors $\eta_1,$ $and\, \eta_2$ are introduced, taking values between 0 and 1. It is adjusted according to the speed of the submersible to make the motion of the submersible more realistic.

$$\eta = 1 - k \times \frac{v - v_{max}}{v_{min} - v_{max}} \tag{4}$$

Effects of ocean current drift. With the loss of power, the submersible will not be able to resist the push of the ocean currents and will have to drift with them. The speed and direction of the currents will determine the drifting trajectory of the submersible, making it difficult to predict and localize. Therefore, the team specifies that $F_{x,}$ i, and $F_{y,i}$ are the cumulative forces in the x and y directions, respectively, with an initial value of 0, and m is the mass of the submersible. Knowing the force on the submersible allows us to calculate the magnitude of its velocity at each step length.

$$F_{x,i} = F_{x,i-1} + F_f \times cos(\alpha) \tag{5}$$

$$F_{y,i} = F_{x,i-1} + F_f \times sin(\alpha) \tag{6}$$

$$v_{x,i} = v_{x,i-1} + \triangle t \times \frac{F_{x,i}}{m} \tag{7}$$

$$v_{y,i} = v_{y,i-1} + \triangle t \times \frac{F_{y,i}}{m} \tag{8}$$

$$v_{h,i} = \sqrt{(v^2{}_{x,i} + v^2{}_{y,i})} \times \eta_2 \tag{9}$$

Impact of seabed topography. The seafloor topography is not flat but has complex geomorphic features such as mountains and canyons. There is a risk that the submersible will collide with obstacles on the seafloor during drifting, resulting in a sudden decrease in speed or even damage. In each prediction step of the model, the position of the submersible is compared with the elevation of its corresponding seafloor to determine whether the submersible has collided or touched the bottom, to more accurately simulate the drifting trajectory of the submersible.

Sinking or upwelling trends. Since the submersible is unable to control its buoyancy after disablement, its weight will cause it to sink or float gradually until it touches the seafloor or reaches the buoyancy neutral surface and floats up and down at its interface. To model the effect of buoyancy, the buoyancy variable F_b is introduced and incorporated into the vertical equation of motion of the submersible.

$$F_{z,i} = mg - F_b \tag{10}$$

$$v_{z,i} = v_{z,i-1} + \triangle t \times \frac{F_{z,i}}{m} \times \eta_1 \tag{11}$$

By using the above Eq.(4) to (11), the force as well as the change in velocity of the submersible is derived and the displacement is solved for each step:

$$\begin{cases} \triangle x = v_{x,i-1} + \frac{1}{2} \times F_{x,i} \times (\triangle t^2) \\ \triangle y = v_{y,i-1} + \frac{1}{2} \times F_{y,i} \times (\triangle t^2) \\ \triangle z = v_{z,i-1} + \frac{1}{2} \times F_{z,i} \times (\triangle t^2) \end{cases} \tag{12}$$

(2) The submersible was only lost: although the submersible lost communication with the outside world, its power system was still functioning normally and it was able to control its navigation autonomously. However, due to the loss of the communication system, the outside world is unable to obtain the position information of the submersible, which brings certain difficulties to the search and rescue operation. In this case, this paper assume that the submersible is still able to navigate autonomously but lacks external localization and guidance, so the following scenarios may occur:

Drift off the intended course. Due to the loss of external positioning and guidance, the submersible may be affected by ocean currents, resulting in sailing off course. The speed and direction of the currents will determine the drifting trajectory of the submersible.

Accumulation of heading errors. Due to the lack of external positioning information, the submersible may accumulate heading errors during navigation, resulting in the final position deviating far from the expected position.

Uncertainty of the state of the submersible. Since the outside world cannot obtain the state information of the submersible, such as sailing speed, depth, etc., the search and rescue personnel cannot accurately understand the current situation of the submersible, which increases the difficulty of search and rescue.

For analysis, it is assumed that after the loss of the submersible, the operator, due to psychological factors, manipulates the submersible to travel vertically toward sea level horizontally and horizontally in the opposite direction of the current to avoid joining the danger zone with the current.

To simulate the random nature of this power, the team used a series of randomly generated angles to determine the angle of direction of the horizontal power and weighted it in such a way as to favor more the angle toward the opposite direction of the current. Additionally, the team used F_m as the submersible's power, which is sized at 20 to 40kN approximately equal to 2,900 to 5,800hp, thus yielding the following set of equations based on the formulas for unpowered conditions:

$$\begin{cases} F_m = 20 + 20 \times rand \\ \theta = (0.5 \times \frac{\pi}{2} + 0.2 \times \pi + 0.2 \times \frac{3\pi}{2} + 0.1 \times 2\pi) \times rand \\ F_{x,i} = F_{x,i-1} + F_f \times cos(\alpha) + F_m \times cos\,\theta \\ F_{y,i} = F_{x,i-1} + F_f \times sin(\alpha) + F_m \times sin\,\theta \end{cases}, i = 1,2...n \tag{13}$$

Where $rand$ denotes a random number in the closed interval [0, 1].

In the vertical direction, the team took into account that the vertical dynamics of the submersible may vary somewhat at different depths, so the team divided the vertical dynamics into the following three phases, stipulating that downward is the positive direction and upward is the negative direction:

$$F_{z,i} = \begin{cases} mg - F_b + 0.01 \times F_b \times rand & h \le -100 \\ -(mg - F_b + 0.001 \times F_b \times rand) & h > -100, v_{z,i-1} \le 0.2 \\ -(mg - F_b + 0.1 \times F_b \times rand) & h > -100, v_{z,i-1} > 0.2 \end{cases}, i = 1,2...n \tag{14}$$

The predictive model provided by the team effectively simulates the complex motions of a submersible in an underwater environment by introducing stochastic factors and depth-dependent behaviors. The flexibility and adjustability of the model parameters allow it to adapt to different submersible types and environmental conditions, thus improving the generalizability of the simulation. In addition, the model has good scalability, which provides a basis for introducing more complex dynamics models, submersible shapes, and control systems in the future, further enhancing the accuracy and realism of the simulation and providing a more powerful tool for submersible SAR and related research.

2.5. Analysis of Results

Based on the above prediction function the trajectories can be derived separately for the two cases, assuming the same lost position of the submersible and the same initial velocity for the two cases, the spreading of the trajectories in the three-dimensional space can be derived, as shown in Figure 5.

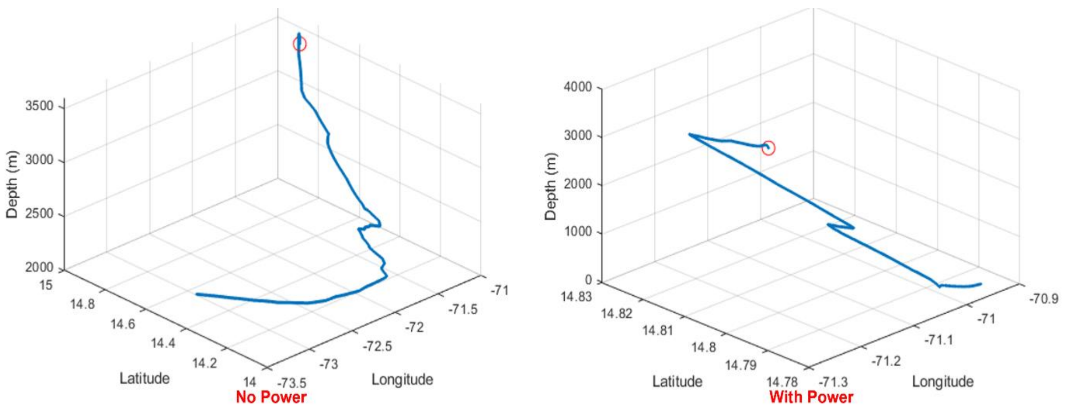

Figure 5. 3D display of trajectory prediction

The above 3D trajectories are merged in the same 3D scene with the seabed topography data to get the displacement route of the submersible motion trajectory in the real terrain, see Figure 6.

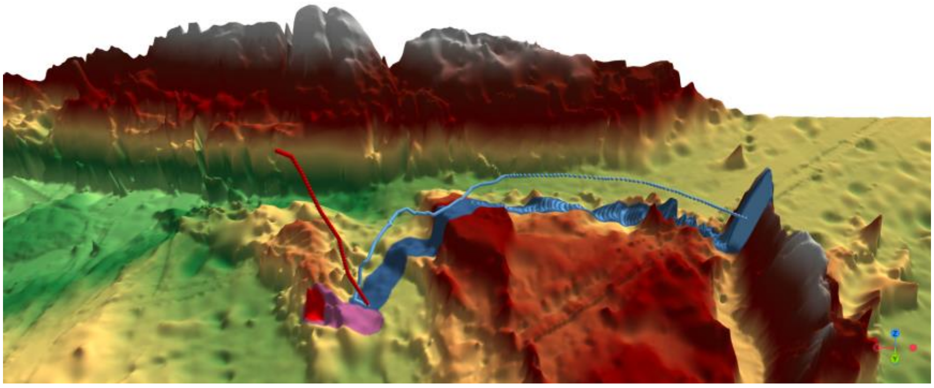

Figure 6. Submersible trajectories in 3D terrain

The Figure 6 compares the predicted trajectories of the submersible underpowered and unpowered conditions.

The blue trajectory represents unpowered drift, in the horizontal direction the submersible is affected by ocean currents and moves in the direction of the currents; in the vertical direction, the submersible initially dives, then floats upward and fluctuates up and down at a certain depth interface under the influence of buoyancy and stops moving at 2,843.22 meters underwater in a collision with a submarine mountain range after 17.93 hours.

The pink track represents powered navigation, where the submersible was less affected by ocean currents and continued traveling upward for 2.43 hours to reach sea level, moving laterally 31,483.01 meters.

The comparison results demonstrate the significant influence of the power system on the trajectory of the submersible. In the unpowered case, the submersible is controlled by environmental factors and the drift trajectory is unpredictable, while in the powered case, the submersible can independently control the heading and the motion trajectory is more controllable. In addition, seafloor topography is critical to the safety of submersibles, and unpowered drifting ultimately leads to collisions between submersibles and seafloor mountains, highlighting the potential threat of seafloor topography to submersible navigation.

Figure 7. Ocean currents and the trajectory of the submersible

This figure demonstrates that the drift trajectory of the submersible under unpowered conditions is highly consistent with the direction of ocean current flow. This indicates that the ocean current is the key factor dominating the drift path of the incapacitated submersible.

The effect of buoyancy on the motion of the submersible is further analyzed by projecting the 3D trajectory onto the xoz plane, see Figure 8:

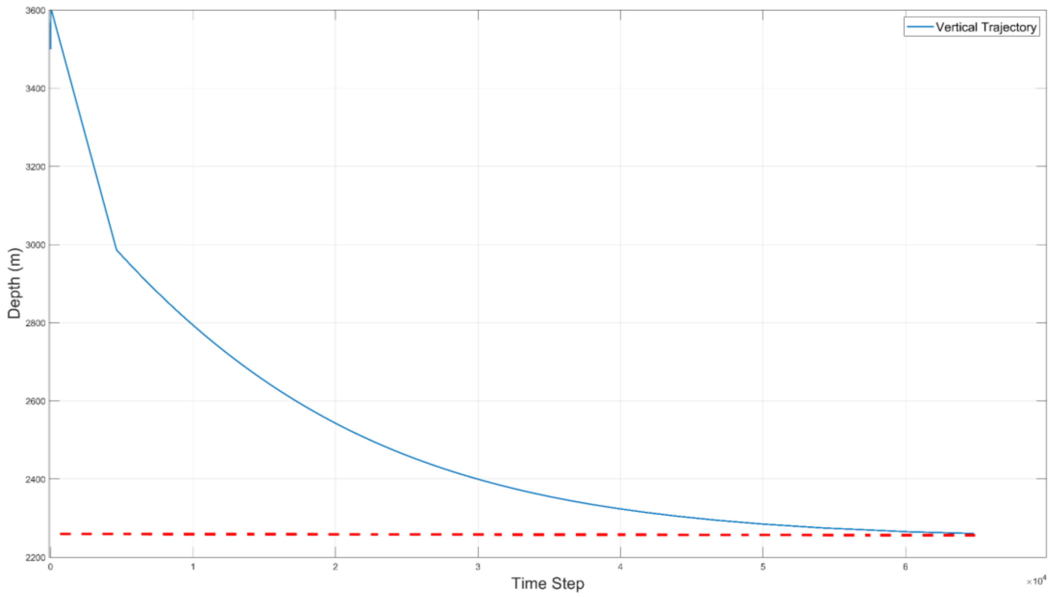

Figure 8. Buoyancy neutral plane

It can be observed in the figure that under unpowered conditions, the motion of the submersible in the vertical direction eventually stagnates at a particular depth and ceases to change. This indicates that the submersible has reached the buoyancy neutral plane, a state in which the gravity and buoyancy of the submersible have reached equilibrium. At this point, the submersible will neither continue to sink nor float, but will fluctuate up and down around that depth.

3. Underwater Search and Path Optimization

3.1. Analysis of Search Methods

To locate the submarine more quickly and accurately after it is lost, the team chose an unmanned aerial vehicle (UAV), one of the most commonly used underwater rescue devices in the market today, as the core device [12], and equipped it with sonar equipment with a wide detection range.

To minimize the search and rescue path and find the submarine with the highest probability, the team guided the search operation by predicting the trajectory of the submarine after it was lost. Every two minutes, a predicted coordinate point was identified, which together formed the most probable set of locations, the maximum probability point set. Other points outside the predicted path are considered to be low probability points for the submarine's presence.

It is now specified that there are z maximum probability points, and the z maximum probability points are randomly numbered. To ensure that the UAV reaches z probability points the total path $f(x)$ is minimized, so the fitness is the inverse of the total path:

$$g(x) = {}^{1}\!/_{f(x)} \tag{15}$$

Calculating the probability that individual i is selected conforms to the following equation:

$$p_i = {}^{f_i}\!/_{\sum_j^N f_i} \tag{16}$$

In the crossover operation, a real number crossover is used and the number of crossovers is determined by the crossover rate, where the kth probability point a_k and the mth probability point at the jth position are subjected to the crossover operation, and the crossover is performed in such a way as to ensure that the ordinal number of the point with the largest probability in each population remains unchanged:

$$\begin{cases} a_{kj} = a_{mj} \\ a_{mj} = a_{kj} \end{cases} \tag{17}$$

In the mutation operation, the number of mutations is affected by the mutation rate, and the ordinal number of the point in the population with the highest probability of mutation is randomly selected. Subsequently, the distance is recalculated and several cycles are performed to find the shortest distance.

To avoid situations such as undersea undercurrents that cause the position of the submersible to shift to reach small probability points, circular search is also introduced into the genetic algorithm, and whenever a maximum probability point is reached while the device is traveling along the shortest path, the device searches the circular area with radius r with that point as the origin. It ensures that the submersible conducts a more comprehensive detection around each maximum probability point to avoid offsetting the position of the submersible resulting in missing important targets.

3.2. Analysis of the Search Situation

Determine a search path and a circular search range for a wrecked submersible divided into two cases: lost and disabled and only lost.

(1) Lost and disabled case: The predicted maximum probability points are divided into groups of 10, each group corresponding to 20 minutes, and the shortest path is searched for each group. For each group of maximum probability point sequences, a genetic algorithm is used to determine the shortest path. In the genetic algorithm, the circular search range r is set to 70m to ensure a comprehensive search of the surrounding area. According to the shortest distance of each group, the UAV was chosen to travel from the surface rescue point to the last predicted point of the first group in a straight line at a speed of 25m/s. Then the search was conducted around this genetic algorithm-derived shortest path, and the circular search was conducted at each passing probability point until the period corresponding to the second group (36 min) in which the submersible was about to enter. the UAV left its current position 2 min ahead of the period for the second group of the last predicted point. Upon arrival, the search is conducted again following the above scheme. The process is repeated until the search stops when the UAV is found.

Underwater rescue follows the principle of proximity and speed, and this paper analyzes the rescue situation within two hours after the crash. In the case of no power, 2 hours can be divided into 6 groups, taking into account the different movement status of the submarine at each moment, the team selected the 2nd group, 4th group, and 6th group for the prediction and calculation of the shortest path, and came up with an average shortest path of 4508m, probably the UAV for each group of the shortest path to travel 5 or 6 laps to find the submarine more quasi-complete. Figure 9 shows the shortest path of group 2 and the circular search path.

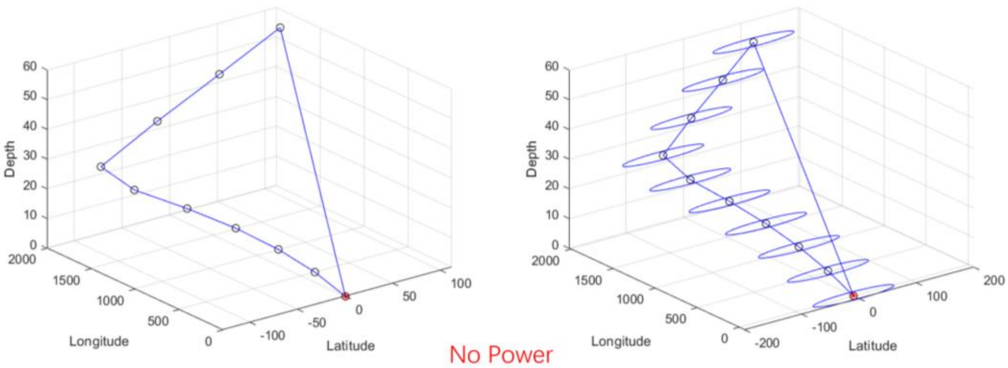

Figure 9. Search for lost and disabled submarine paths

(2) Lost only case: considering the impact of the power of the submarine, the UAV, to find it more accurately, will predict the maximum probability of the point, every 6 groups, each group corresponds

to 12 minutes, to carry out the search for the shortest section of the path, and set the circular search range r at 70m.

In the case of power, 2 hours can be divided into 10 groups, the team selected the 3rd group, 6th group, and 10th group for the prediction and calculation of the shortest path, and the average shortest path is 5437m, probably the UAV for each group of the shortest path to travel 2 or 3 circles, at this time, you can increase the speed of the UAV, to make it more quasi-deserted to find the submarine. Figure 10 shows the shortest path of group 3 and the circular search.

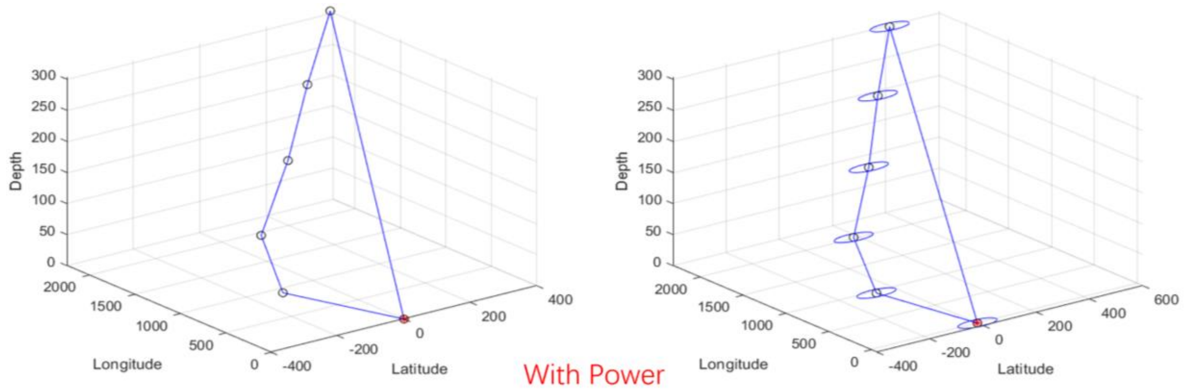

Figure 10. Searching for the path of a lost submersible only

4. Conclusion

Determining the position of a submersible at different times in a known sea area is a nonlinear prediction problem. For the prediction of the position of the submersible in the deep sea, it is necessary to consider the relationship between seawater topography, ocean currents, seawater density, and also the speed and direction of movement of the submersible at the time of the collision, so the team modified the logistics regression model to predict the position of the submersible in different periods based on the energy loss model and the ocean current prediction model. According to MATLAB's solution of the latitude and longitude prediction model, after 17.93 hours of the lost connection and loss of energy, the submersible arrived at the seafloor at a water depth of about 2,843.2m. The lost-only submersible reached sea level after 2.43 hours and moved 31,483.01m laterally. The team designed a localization prediction model that applies to multiple simultaneous submersible wreck situations and can be applied to a variety of fields such as underwater rescue and underwater search.

In terms of search, a search model based on a genetic algorithm was established. The search position interval is determined based on the predicted path of the wrecked submersible, and the shortest path for search and rescue is calculated using a UAV as the search equipment. According to the calculation results, the average shortest path for the search of a lost disabled submersible is 4508m, and the average shortest path for the search of only a lost submersible is 5437m. The search and rescue time and route are determined based on the predicted trajectory. Compared with the large-scale carpet search and rescue mode, it greatly saves search and rescue resources and improves the efficiency and success rate of search and rescue work.

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