Proceedings of the 2nd International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/74/20240497

Marine management and monitoring system based on AHP cost-benefit analysis with integrated evaluation and genetic algorithms for recurrent searches

Zhuangzhuang Yuan

School of Electrical Engineering, Shenyang University of Technology, Liaoning, Shenyang, 110870, China

1186356900@qq.com

Abstract. Marine management and monitoring systems need to develop a safety procedure for submersibles that predicts changes in the position of the submersible over time. This would effectively prevent the submersible from losing communication with the host and would allow it to react to possible deficiencies. In this paper, a random walk model is used to predict the position of the submersible at each moment on the seafloor. The probability of the highest point on each plane is 0.87-0.92. The error in the position of the submersible caused by the uncertainty on the seafloor is corrected by the Kalman filter model. In this paper, we use AHP cost-benefit analysis to comprehensively evaluate and select the best additional search equipment. In this paper, the genetic algorithm based on cyclic search is used to determine the optimal initial deployment point and search pattern. After a large number of iterations, the shortest search path length of 817.273 is obtained, and the shortest search path is taken as the optimal path for search and rescue. In this paper, the model is extended using particle swarm algorithm and environment modelling. The predictive model of the submersible is combined with the environmental model of different sea areas. Therefore, the actual motion model of the submersible is approximated. After simulation, it was found that the accuracy of the submersible probability increased by 23.72%.

Keywords: Marine management, AHP, Genetic algorithms.

1. Introduction

Maritime Cruises Mini-Submarines (MCMS), based in Greece, specialises in building submersibles capable of transporting humans to the deepest depths of the ocean [1]. The company is planning a bold new adventure - using their submersibles to take travellers on fascinating expeditions to explore shipwrecks on the floor of the Ionian Sea [2]. However, before embarking on these exciting journeys, MCMS needs to gain approval from regulatory bodies [3]. To do this, they must have comprehensive safety measures in place to deal with situations such as loss of communication with the host vessel or potential mechanical failures, including loss of propulsion of the submersible [4].

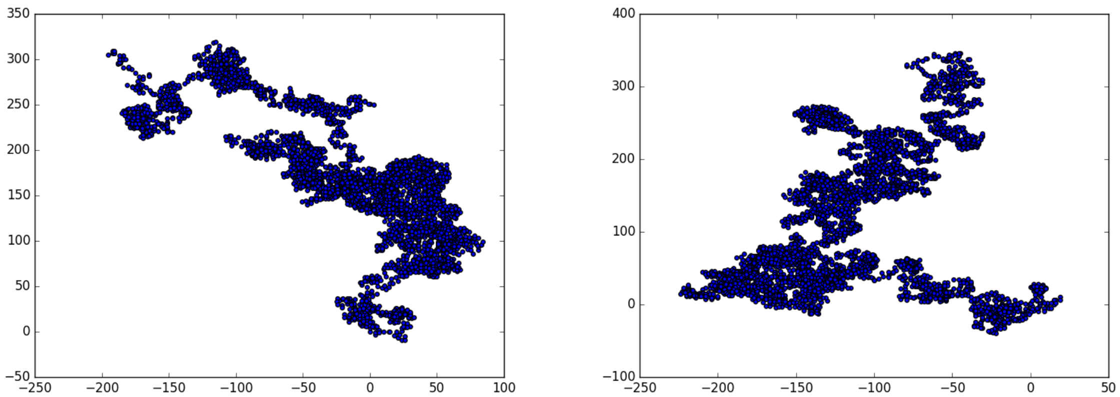
Key parts of the safety procedures include predicting the position of the submersible over time and developing a model to guide the search pattern if the submersible is lost [5]. The unique challenges of underwater exploration, such as varying seafloor geography, varying sea densities and currents, add to the complexity of this task [6].

DOI: 10.54254/2755-2721/74/20240497

The goal of this paper is to execute this ambitious project while prioritising safety, efficiency and compliance with regulatory requirements.

2. Position probability distribution

Refer to the random walk model and incorporate the relationship between the position at the current moment and the position at the previous moment. Draw a probability distribution of the position of the submersible on the seafloor. As shown in the figure 1:



Random walk simulation results I

Random walk simulation results II

Figure 1. Random walk model simulates submersible location.
(Photo credit: Original)

Referring to a Bayesian probabilistic model, integrating the uncertainties of ocean currents, seafloor topography, ocean density, and data loss, the probability of a submersible's presence in the three-dimensional space is predicted, giving the following probability distribution. The probability location distribution of the submersible is shown in Figure 2:

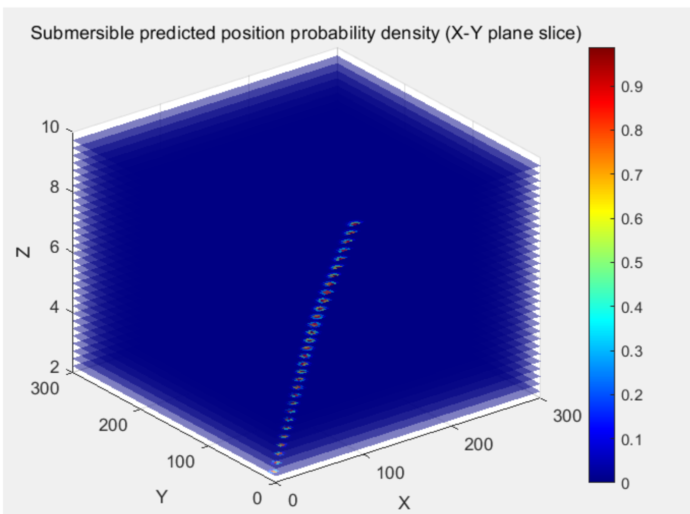


Figure 2. Distribution of possible locations of submersibles.
(Photo credit: Original)

It can be seen from the figure,the probability of the submersible appearing in each position in three-dimensional space is higher or lower.The probability distribution of the position of the submersible at each moment forms a trajectory line.

3. AHP-cost-effectiveness portfolio evaluation

Table 1. Cost-effectiveness ratios for search and rescue equipment.

Search and rescue equipment	Wireless sonar - Ultrasonic detection	SDDTMB Beidou BDGPS receiver	AR944A+ Hema Sounder	ADIS16460 inertial navigation system	HK90B HD underwater camera
CER	0.010383	0.071306	0.018528	0.018528	0.004430

From the analysis of the above table we can see that the best SAR equipment is the SDDTMB Beidou BDGPS receiver.

4. Genetic Algorithm for Circular Search

First, we use the point with the highest probability in the Bayesian probability density map in the prediction model as the reference point for the search to perform a circular search, and the search radius increases with time [7]. Here we assume that the position of the reference point is (h, k), then the search area at time t can be represented by the following function:

$$(x-h)^2+(y-k)^2=r(t)^2 \tag{1}$$

where x is the independent variable, y is the dependent variable, h is the horizontal coordinate, k is the vertical coordinate, r is the search radius [8]. The following introduces the search radius formula:

$$r(t)=r_0+v^*t \tag{2}$$

where v is the traversal speed, t is the traversal time, and r_0 is the initial search radius. By combining (3.8) and (3.9) we obtain:

$$(x-h)^2+(y-k)^2=(r_0+v^*t)^2 \tag{3}$$

With this in mind, we draw the path planes of the critical points obtained from the circular search.as shown in the figure.

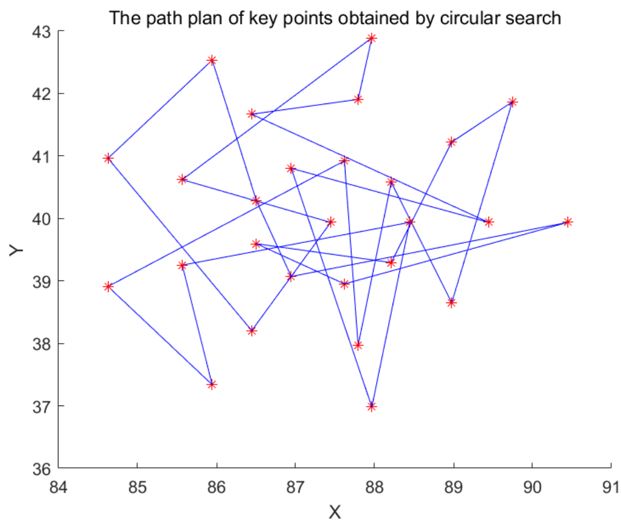


Figure 3. Path plan of critical points.
(Photo credit: Original)

On this basis, we use the genetic algorithm model based on circular search to iterate the key points obtained from the above figure to find out the shortest path that traverses all the key points, so we can get the three-dimensional path diagram that traverses all the key points, as shown in the following figure:

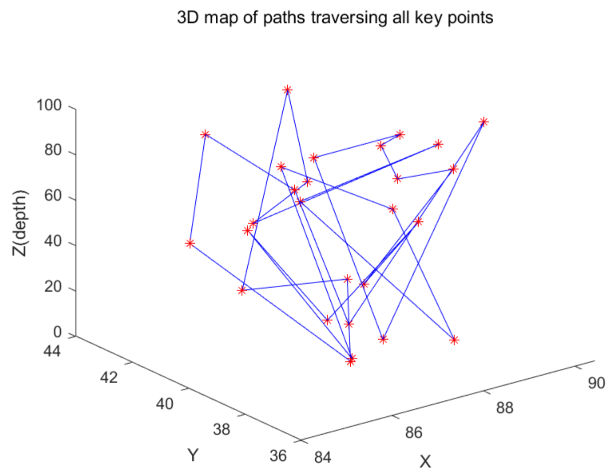


Figure 4. Traverse the 3D path diagram of all critical points.
(Photo credit: Original)

By getting the shortest path, we can minimize the time to find the missing submarine.

5. Extended model for environmental parameter tuning

We take the marine environmental parameters of the Caribbean Sea as an example, first of all, we will set the position of the submersible in two different seas as the same position, that is, at the same depth in the sea, change the friction coefficient of the currents in different seas, the external driving force and the coefficients of the influence of currents on the speed of the different seas to map the position of the submersible in the two seas to move the trajectory of the movement of the trajectory is shown in the figure below:

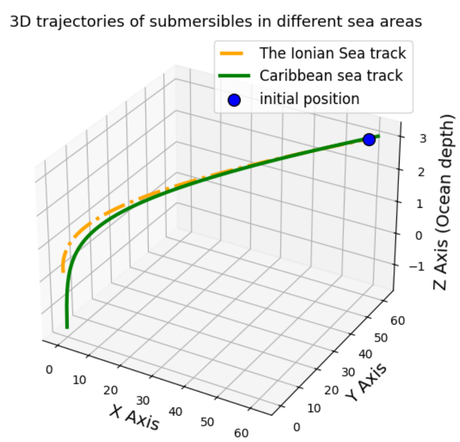


Figure 5. Trajectories of submersible position movements in two oceanic areas.
(Photo credit : Original)

From the above figure, it can be seen that when the submersible is in different sea areas, even if the relative depth of the submersible is kept the same at the beginning, the subsequent positional trajectories of the submersible are deviated due to the different parameters of the marine environment in different sea areas, these deviations are important for the model to be extended to the optimization of different tourist destinations, so we choose the model of the continuous motion system of the currents after the currents have been taken into account [9].

6. Multi-submersible position prediction and tracking

In the previous position model, we predicted the position trajectory of a submersible in a fixed sea area of the Ionian Sea, but in the actual sea area, the interaction of multiple submersibles should be taken into account, so we introduced the interaction term between multiple submersibles in the previous position model. At the same time, among multiple submersibles in the same sea area, we select the four submersibles with the highest position probability and the strongest correlation for the position prediction and tracking of multiple submersibles. We can get the 3D motion trajectory diagrams of the four target submersibles as shown in Figure:

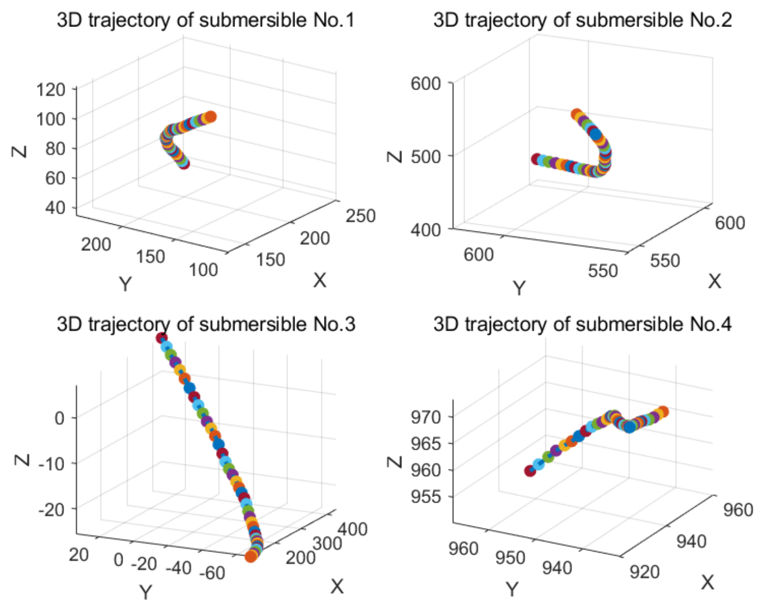


Figure 6. Three-dimensional trajectories of four target submersibles.
(Photo credit : Original)

It can be seen from the above figure, and according to assumption three, for multiple submersibles in the same sea area, after we substitute the interaction term between multiple submersibles into the positional model, we will get the positional trajectory of each submersible, and after grasping these results, we can carry out a reasonable planning to avoid collision prone phenomenon in the process of tracking each submersible.

7. Strengths and Weaknesses

7.1. Strengths

To more accurately model future trends when performing probabilistic analyses, we apply stochastic parameters to the model to capture the effects of currents. We set random elements to randomly generate values that follow a normal distribution without errors due to incorrect constants or omitted variables.

Through simulations, we find that our model makes significant progress in predicting probabilistic metrics for the submersible after incorporating a continuous dynamic system of ocean currents. This shows that our model is effective.

For different sea areas and different cases of diver numbers, our model can get reasonable results with strong robustness.

DOI: 10.54254/2755-2721/74/20240497

7.2. Weaknesses

Although our model considers the problem indicators very comprehensively, due to the missing data of some indicators, we can only choose the indicators with real and complete data to analyze, which will lead to the problem of poor data accuracy due to the small amount of data.

The model does not consider the occurrence of sudden events. Many unexpected things may happen in reality. For example, natural disasters such as typhoons and tsunamis may arise during search and rescue. The strategy must quickly adapt to the changing series of events in order to better achieve the goal of finding the submersible as soon as possible.

References

[1] Franceschetti, Massimo,Jehoshua Bruck, and Leonard J. Schulman. "A random walk model of wave propagation." IEEE transactions on Antennas and Propagation 52.5 (2004): 1304-1317.

[2] Cheung,Sai Hung,and James L.Beck."Calculation of posterior probabilities for Bayesian model class assessment and averaging from posterior samples based on dynamic system data." Computer Aided Civil and Infrastructure Engineering 25.5 (2010): 304-321

[3] Lee, Jay H., and N. Lawrence Ricker. "Extended Kalman filter based nonlinear model predictive control."Industrial&Engineering Chemistry Research 33.6 (1994): 1530-1541.

[4] Masreliez,Cl,and R. Martin."Robust Bayesian estimation for the linear model and robustifying the Kalman filter ."IEEE transactions on Automatic Control 22.3 (1977): 361-371.

[5] Mirjalili,Seyedali,and Seyedali Mirjalili."Genetic algorithm."Evolutionary Algorithms and Neural Networks: Theory and Applications (2019): 43-55.

[6] Malkawi, AI Husein, Waleed F.Hassan, and Sarada K. Sarma . "An efficient search method for finding the critical circular slip surface using the Monte Carlo technique." Canadian Geotechnical Journal 38.5 (2001): 1081-1089.

[7] Sahoo, Mrunmayee M.,etal."Evaluation of water quality with application of Bayes' rule and entropy weight method."European Journal of Environmental and Civil Engineering 21.6 (2017): 730-752.

[8] Franceschetti, Massimo,Jehoshua Bruck,and Leonard J.Schulman."A random walk model of wave propagation."IEEE transactions on Antennas and Propagation 52.5 (2004): 1304-1317.

[9] Marini, Federico,and Beata Walczak."Particle swarm optimization(PSO).A tutorial." Chemometrics and Intelligent Laboratory Systems 149 (2015): 153-1 65.