Positioning and Search System for Submersibles: Model Construction, Results, and Future Prospects

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Abstract. This paper proposes a comprehensive positioning and search system for deep-sea submersibles to enhance efficiency in complex marine environments. The core position prediction model integrates Kalman and extended Kalman filters, accounting for submersible dynamics and geographical data. This approach effectively addresses nonlinear challenges from forces like buoyancy, gravity, ocean currents, and resistance. High-precision positioning on 3D topographic maps is achieved through optimized dynamic and observation equations.Equipment selection utilizes the TOPSIS model to evaluate eight deep-sea rescue tools, emphasizing functionality, cost-effectiveness, safety, and durability. Search efficiency is improved by integrating the position prediction model with the ant colony algorithm, reducing search paths and time in simulations. A multi-target cooperative position prediction model, incorporating multi-target and cooperative extended Kalman filters, supports multi-submersible coordination.Environmental adaptability is demonstrated in areas like the Caribbean and Ionian Seas, highlighting the model's robustness. While significant progress has been made, challenges remain in ensuring accuracy, stability, and feasibility in extreme conditions. Future research will focus on data collection, parameter optimization, and developing more efficient algorithms to expand the model's applicability in diverse marine scenarios.

Keywords: Submersible, Position prediction, TOPSIS, Search model, Model extension

1 Introduction

The development of submersible technology has revolutionized ocean exploration, offering a powerful tool for understanding the underwater world. Greek company MCMS has launched an advanced submersible for exploring shipwrecks in the Ionian Sea, but challenges such as mechanical failures and loss of contact with the mother ship pose serious risks to safety, financial stability, and reputation. Addressing these challenges is crucial to ensuring the success of such projects.

This research holds significant theoretical and practical importance, enriching the system of submersible positioning, searching, and rescuing in complex marine environments. By developing innovative models and algorithms, it enhances understanding of submersible-environment interactions and improves position prediction, contributing to the broader advancement of marine technology.

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The study aims to create a practical positioning and search system to ensure safety and efficiency across diverse marine environments and multi-submersible scenarios. A robust position prediction model, considering factors like buoyancy, ocean currents, seawater density, and seafloor geography, is essential. Addressing uncertainties improves prediction accuracy and informs equipment selection for both mother and rescue ships. A search and rescue model will optimize deployment points and search patterns, minimizing response times. Leveraging accumulated data, it calculates the probability of finding submersibles over time for targeted rescues. The models must adapt to varying sea conditions and multi-submersible operations, ensuring reliability in diverse environments. This research aims to enhance operational safety, efficiency, and rescue success rates, contributing to the advancement of ocean exploration technology.

2 Related Work

In the field of research related to submersible positioning and search rescue, several important techniques and models have been studied and applied in different contexts.

Kalman filtering and its extended forms have been widely used in various fields such as aerospace and robotics navigation [1]. In these applications, they have demonstrated their effectiveness in estimating the state of dynamic systems [2]. However, when applied to the submersible domain, significant adjustments are required to account for the unique characteristics of the marine environment [3]. The complex and variable nature of the ocean, including factors such as currents, salinity, and temperature gradients, demands a more tailored approach to ensure accurate position prediction of submersibles [4].

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) model has been a prominent tool in multi-criteria decision analysis [5]. It has been applied in numerous scenarios where multiple factors need to be considered for evaluating alternatives. In the context of submersible equipment selection, it provides a framework for comparing different equipment options . However, it is crucial to adapt this model to the specific requirements of the submersible search and rescue scenario [6]. This involves carefully determining the relevant evaluation criteria and their respective weights based on the actual conditions and needs of the operation. For example, factors such as equipment functionality, cost, reliability, and durability need to be considered in a balanced manner to make an informed decision [7].

Weighted networks and ant colony algorithms have been extensively studied for path search and optimization problems[8]. These algorithms have shown promising results in finding optimal paths in various complex environments [9]. When applied to the search and rescue operations in the marine environment for submersibles, they face several challenges due to the complexity of the oceanic setting. The vastness of the ocean, the presence of multiple obstacles, and the dynamic nature of the environment require sophisticated modifications to these algorithms to ensure their effectiveness. The algorithms need to be able to handle the uncertainties associated with the submersible's position, the changing ocean currents, and the varying visibility conditions [10].

Current submersible positioning and rescue research for the Ionian Sea and MCMS project faces limitations. Key challenges include neglecting factors like seafloor topography and submersible interactions, inadequate equipment evaluation methods, and unoptimized rescue models, leading to safety risks and slower response times in complex marine environments.

3 Research Methods

3.1 Position Prediction Model Construction

To predict the position of the submersible, we utilize Kalman filtering and its extended form to integrate sensor information. Firstly, a dynamic physical model is established, taking into consideration the forces acting on the submersible and geographical environmental factors. The forces include buoyancy, gravity, current force, and resistance. Based on these factors, dynamic and observational equations are constructed. To address the nonlinear problems, improvement measures are introduced, and the model is extended to the extended Kalman filtering form. This allows for a more accurate prediction of the submersible's position in the complex marine environment.

3.2 TOPSIS Model Application

The entropy weight method is employed to determine the weights for a comprehensive evaluation of four aspects of deep-sea rescue equipment Figure 1 provides a visual representation of the comprehensive evaluation process of the TOPSIS model [5].

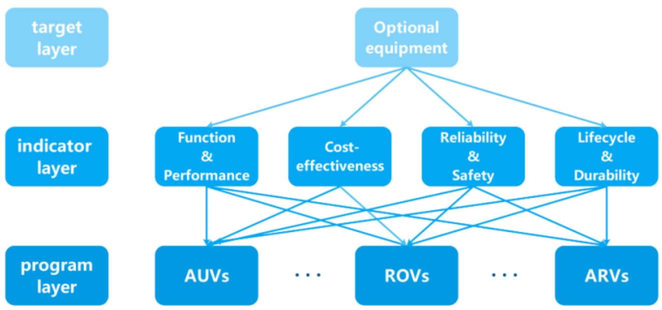

Fig. 1. TOPSIS Model

These four aspects typically include functionality and performance, cost-effectiveness, safety, and durability. By calculating the weights for each aspect, a more objective and comprehensive evaluation of the equipment can be achieved.

3.3 Search Model Construction and Optimization

Traditional Search Model: Data related to the submersible is collected, including its last communication location, motion vector, current velocity, and direction of the ocean current. Based on this data, a vector synthesis model is constructed to determine the initial search direction.

Novel Search Model: This model combines the position prediction model and the ant colony algorithm. Relevant parameters are defined to optimize the search path. The ant colony algorithm is introduced to consider the pheromone concentration, distance vector, and direction vector, etc. These parameters are adjusted according to the predicted position to improve the search efficiency.

4 Data Collection and Processing

4.1 Data Collection

These data are sourced from the global ocean model dataset, such as GEBCO 2023. The dataset provides information on various geographical environmental factors, including seawater temperature, ocean current strength, and seafloor topography. This data is crucial for understanding the environment in which the submersible operates, as shown in Figure 2, which presents a detailed view of the geographical environment data, such as the distribution of seawater temperature and ocean current strength.

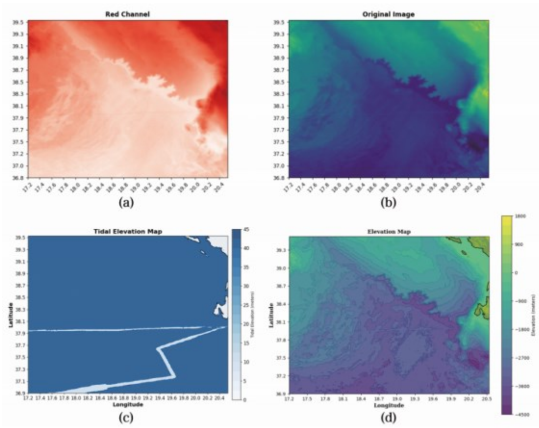

Fig. 2. Marine Environment Map Group

Data related to the submersible is collected through internal and external sensors. Internal sensors may include inertial measurement units (IMU), while external sensors can be sonar devices and GPS buoys. These sensors provide information on the submersible's position, velocity, and attitude. This data collection process is essential for accurately predicting the submersible's position and movement.

Information about equipment is obtained through literature search. This includes details about the functionality, performance, cost, and other characteristics of different types of equipment used in deep-sea rescue operations.

4.2 Data Processing

Sensor data for the position prediction model undergoes preprocessing (cleaning, normalization, transformation) for compatibility with Kalman filtering algorithms. For the TOPSIS model, equipment data is normalized, and indicators like entropy weight are calculated for evaluation. Predicted values are integrated with the ant colony algorithm to optimize search paths.

5 Experimental Results

5.1 Position Prediction Model

A position prediction model integrating Kalman and extended Kalman filtering techniques accounts for submersible dynamics, including buoyancy, gravity, currents, resistance, seawater density, and seafloor topography. Refined dynamic and observational equations ensure accurate predictions on 3D topographic maps. Figure 3 shows alignment with actual seabed features, while Figure 4 highlights analyzed uncertainties like sensor errors, process noise, and unmodeled dynamics, enhancing prediction reliability.

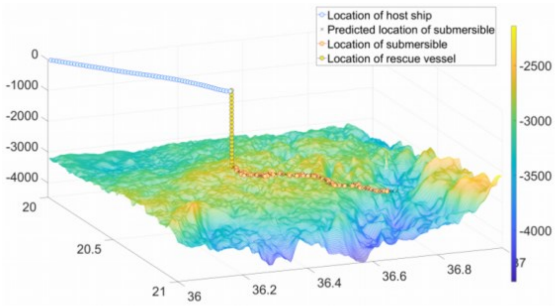

Fig. 3. Location Prediction Model

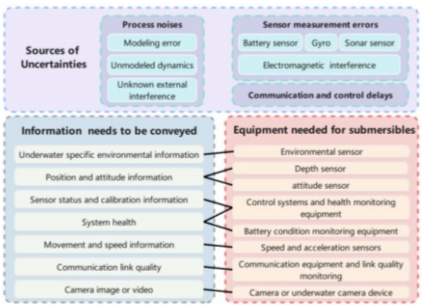

Fig. 4. Uncertainty Analyses

In various simulated scenarios, the model has demonstrated its adaptability and effectiveness. For example, in scenarios with different current velocities and directions, the model was able to adjust its predictions accordingly. The data shows that as the current velocity increased, the predicted position of the submersible deviated more from its initial position, but the model was still able to capture the general trend of the movement. In scenarios with varying seafloor topographies, such as slopes and ridges, the model accounted for these changes and provided more accurate predictions near the complex terrain areas.

5.2 TOPSIS Model

The TOPSIS model was applied to evaluate 8 types of deep-sea rescue equipment. By using the entropy weight method, weights were assigned to four key aspects: functionality and performance, cost-effectiveness, safety, and durability. This process involved a series of calculations, starting from data normalization of each equipment's performance indicators to the determination of information entropy and entropy weights.

The comprehensive evaluation results revealed significant differences among the equipment. The weights for functionality and performance, cost-effectiveness, safety, and durability were calculated as 0.5021,0.1984,0.1376,0.1619. The final comprehensive scores for each equipment were as follows: Automated Underwater Robots (AUVs) scored 0.2791, Remotely Operated Vehicles (ROVs) scored 0.1710, and so on. These scores indicate that AUVs and ROVs generally outperformed the other equipment in terms of the overall evaluation, considering all aspects.

5.3 Search Model

The traditional search model, based on submersible data like last communication location, motion vector, and ocean currents, used vector synthesis and a weighted network to determine search paths. While effective in simpler environments, it struggled with strong currents or complex seabed topographies, leading to longer search times and less optimal paths.

The novel search model, integrating the position prediction model and the ant colony algorithm, demonstrated superior performance. By using predicted position data and optimizing search paths with the ant colony algorithm, it adapted effectively to environmental changes. As shown in Figure 5, the novel model achieved significantly shorter search paths and reduced search times compared to the traditional model. This highlights its enhanced efficiency and accuracy, making it more suitable for complex marine environments.

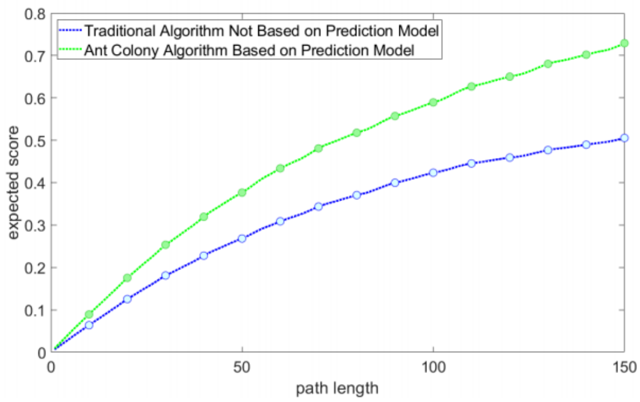

Fig. 5. Evaluation Results

6 Conclusions

In conclusion, a comprehensive submersible positioning and search system has been successfully constructed, incorporating multiple models and their extensions. While achieving certain results in various aspects, the research also has limitations. The models need to improve accuracy and stability in complex environments, optimize equipment selection indicators and weights, and further study the feasibility and complexity of the search model in extreme environments. Future prospects include collecting more data, introducing advanced technologies for optimization, researching better equipment evaluation methods, and exploring efficient algorithms to expand the application range of the models.

References

[1] Simon D. Kalman filtering[J]. Embedded systems programming, 2001, 14(6): 72-79.
[2] Chui C K, Chen G. Kalman filtering[M]. Berlin, Germany: Springer International Publishing, 2017.
[3] Grewal M S, Andrews A P. Kalman filtering: Theory and Practice with MATLAB[M]. John Wiley & Sons, 2014.

[4] Sorenson H W. Kalman filtering techniques[M]//Advances in control systems. Elsevier, 1966, 3: 219-292.
[5] Lai Y J, Liu T Y, Hwang C L. Topsis for MODM[J]. European journal of operational research, 1994, 76(3): 486-500.
[6] Behzadian M, Otaghsara S K, Yazdani M, et al. A state-of the-art survey of TOPSIS applications[J]. Expert Systems with applications, 2012, 39(17): 13051-13069.
[7] Papathanasiou J, Ploskas N, Papathanasiou J, et al. Topsis[M]. Springer International Publishing, 2018.
[8] Karaboga D, Akay B. A comparative study of artificial bee colony algorithm[J]. Applied mathematics and computation, 2009, 214(1): 108-132.
[9] Newman M E J. Analysis of weighted networks[J]. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics, 2004, 70(5): 056131.
[10] Barrat A, Barthelemy M, Pastor-Satorras R, et al. The architecture of complex weighted networks[J]. Proceedings of the national academy of sciences, 2004, 101(11): 3747-3752.