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A Multi-Factor Coupled Framework for Maritime Survival Assessment and Drift Prediction

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Abstract

Maritime emergency rescue faces significant challenges due to high uncertainty in target localization and the difficulty of quantitatively evaluating survival states. To address these issues, a coupled multi-factor framework is proposed for maritime survival assessment and drift prediction. It integrates environmental dynamics with individual physiological and psychological characteristics through a time-dependent coupling mechanism. A current–wind coupled model is employed for trajectory prediction. A trajectory–survival co-evolution framework is introduced to capture the dynamic interaction between spatial drift and survival degradation. The proposed framework is further implemented within a simulation platform to support dynamic anal-ysis and visualization. Simulation results indicate that the proposed framework provides more consistent and robust trajectory prediction under the constructed maritime conditions. Under ±5% environmental perturbations, trajectory deviation remains within 8% and survival variation is below 6%, with relative per-formance improvements of approximately 10%–15% compared with baseline simulation models under the constructed experimental settings.

Keywords

Maritime Emergency Rescue; Survival State Assessment; Trajectory Prediction; Multi-Factor Fusion; Simulation System.

1. Introduction

1.1. Research Background and Motivation

With the rapid development of maritime transportation, fisheries, and offshore engineering, maritime emergency incidents have become increasingly frequent. In scenarios such as man-overboard events and shipwrecks, rapid localization of distressed individuals and reliable survival assessment remain critical challenges for rescue operations.

In practice, trajectories are influenced by wind, ocean currents, and water temperature, leading to significant spatial uncertainty that evolves over time. At the same time, physiological conditions deteriorate due to cold-water immersion and physical exhaustion, making survival time difficult to estimate. The coupling between trajectory uncertainty and survival degradation makes traditional experience-based rescue strategies insufficient under complex conditions.

To address these challenges, modeling and simulation approaches are required to jointly describe environmental influences and individual variability. Trajectory prediction can reduce search areas and improve rescue efficiency, while survival state assessment provides quantitative support for rescue prioritization. Therefore, an integrated framework that combines trajectory prediction and survival assessment is essential for maritime emergency analysis.

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1.2. Related Work

Existing studies on maritime trajectory prediction mainly rely on physics-based models such as Leeway models and operational systems [1,2], which capture large-scale motion but show limited accuracy under complex environmental conditions. Recent research has introduced stochastic and data-driven methods to improve prediction performance, yet the coupling of multiple environmental factors remains insufficient [3,4,5]. In addition, optimization-oriented studies provide complementary perspectives for SAR operations [6]. Recent deep learning-based approaches have further improved prediction accuracy using multi-source ocean data [7].

In survival assessment, prior work primarily focuses on physiological mechanisms such as hypothermia and exposure duration [8,9,10]. These approaches are often based on single-factor analysis and lack dynamic modeling of interactions between environmental and human factors.

Although some simulation systems have been developed, most of them focus on either trajectory prediction or training applications, with limited integration of survival assessment and trajectory modeling [11,12]. As a result, a unified framework that supports multi-factor coupling and dynamic evolution is still lacking.

Overall, current research faces three key limitations. First, multi-factor coupling is insufficient, making it difficult to capture the combined effects of environment and individual variability. Second, survival assessment methods are often static and lack dynamic evolution modeling. Third, the integration between analytical models and simulation systems is limited, reducing practical applicability in engineering scenarios.

1.3. Contributions

To address the above challenges, this paper proposes an integrated framework that combines trajectory prediction and maritime survival state assessment under a unified modeling scheme. A multi-factor survival assessment model based on the Analytic Hierarchy Process is developed to quantify the combined effects of environmental and individual factors. Meanwhile, a trajectory prediction method driven by ocean environmental data is designed to simulate the dynamic movement of distressed individuals. Based on these models, a hierarchical simulation system is implemented to support data processing, model computation, and visualization.

The main contributions of this work are as follows. First, a time-dependent multi-factor coupling mechanism is proposed to model the interaction between environmental dynamics and human survival processes, addressing the limitation of weak coupling in existing studies. Second, a trajectory–survival co-evolution framework is developed to enable integrated analysis of drifting behavior and survival dynamics under changing environmental conditions. Third, an integrated simulation system is implemented to bridge theoretical modeling and practical applications, improving the potential applicability of the proposed approach in maritime emergency analysis.

2. Modeling Framework of Maritime Survival

2.1. Problem Formulation and System Framework

Maritime distress scenarios involve complex environmental conditions and high uncertainty, where both trajectories and survival states evolve dynamically. The motion of distressed individuals is influenced by ocean currents, wind, and waves, while survival capability depends on physiological and psychological conditions. Therefore, a unified modeling framework that integrates environmental dynamics with individual factors is required.

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This study focuses on two key problems: (1) trajectory prediction, which estimates the position evolution under environmental forcing; and (2) survival state assessment, which evaluates survival capability under coupled environmental and individual conditions.

To ensure computational tractability, several assumptions are adopted. Environmental parameters are assumed quasi-stationary within short time intervals (approximately one hour), and individuals are modeled as passive drifting particles driven by currents and wind. Physiological processes are simplified using representative parameters such as body weight, initial condition, and water metabolism rate.

Based on these formulations, a layered framework is developed, consisting of a data layer, a model layer, and a presentation layer. The data layer provides environmental and individual inputs, the model layer integrates trajectory prediction and survival assessment, and the presentation layer supports visualization and interaction. The trajectory and survival models are coupled through shared environmental inputs, enabling integrated analysis of drifting behavior and survival evolution.

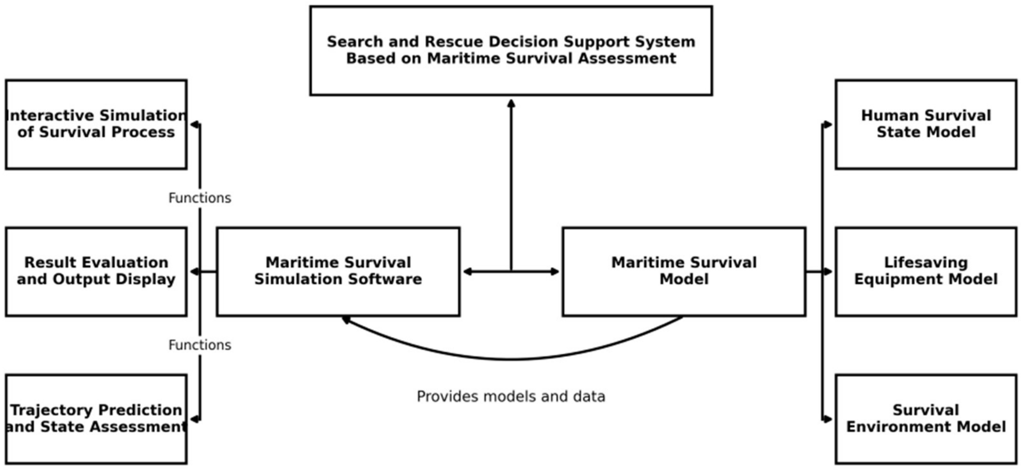

Fig. 1 Overall framework of the maritime survival simulation system with coupled trajectory prediction and survival assessment.

2.2. Data and Parameter Description

The model incorporates both environmental and individual parameters. Environmental inputs include sea surface temperature, wind velocity, and ocean current fields, obtained from publicly available datasets such as IMMA and ocean circulation models [13,14]. Spatial–temporal interpolation is applied to ensure continuity of environmental variables during simulation. To evaluate robustness, a ±5% perturbation is introduced, resulting in trajectory deviations within 8% and survival variations below 6%.

Individual parameters include body weight, height, age, and initial physical condition. A standard basal metabolic rate (BMR) model is adopted to initialize energy consumption based on these personal attributes. In addition, a baseline water metabolism rate is defined to characterize dehydration effects. By integrating environmental and individual parameters, the model provides a unified data foundation for both trajectory prediction and survival assessment.

3. Drifting Trajectory Prediction Model

When distressed individuals lose active control, their motion on the sea surface is primarily governed by ocean currents and wind forcing. The drifting process can be approximated as a coupled dynamic system driven by current-induced transport and wind-induced drift.

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A Lagrangian framework is adopted, where the individual is modeled as a passive particle advected by the flow field. The velocity is expressed as:

$$v(t) = v_c(t) + \alpha v_w(t) \tag{1}$$

where $v_c(t)$ and $v_w(t)$ denote ocean current and wind velocity, respectively, and α is the wind drift coefficient. Based on empirical studies, $\alpha \in [0.01, 0.05]$. In this study, $\alpha = 0.03$ is used, which is selected as a representative value for simplified human drifting simulation.

The trajectory is obtained by integrating the velocity field:

$$P(t) = P_0 + \int_0^t (v_c(\tau) + \alpha v_w(\tau)) d\tau \tag{2}$$

where P_0 is the initial position.

For discrete environmental data, a first-order explicit Euler scheme is adopted:

$$P_{k+1} = P_k + (v_c^k + \alpha v_w^k)\Delta t \tag{3}$$

This formulation ensures computational efficiency and is suitable for efficient iterative simulation. In implementation, the trajectory is computed iteratively using interpolated environmental data, enabling continuous trajectory evolution under varying conditions.

4. Maritime Survival State Assessment Model

4.1. Framework Overview

Maritime survival is governed by coupled environmental and human factors. To enable structured modeling, the Analytic Hierarchy Process (AHP) is adopted to construct a multi-level framework integrating physiological, psychological, and environmental components [15].

The model consists of two main parts: the human survival state model and the environmental model, which interact dynamically during simulation. AHP is used to determine factor weights through pairwise comparison and consistency verification (CR < 0.1). Based on domain characteristics, physiological and psychological weights are set to 0.6 and 0.4, respectively.

4.2. Human Survival State Model

The overall survival state is defined as a weighted combination of physiological and psychological components:

$$S(t) = w_1 L(t) + w_2 X(t), w_1 + w_2 = 1 \tag{4}$$

where $S(t)$ denotes the overall survival state at time t, $L(t)$ represents the physiological state, and $X(t)$ denotes the psychological state. The weights w_1 and w_2 satisfy $w_1 + w_2 = 1$.

For practical interpretation, the survival state is divided into four levels: high ($S > 0.75$), moderate ($0.5 < S \le 0.75$), low ($0.25 < S \le 0.5$), and critical ($S \le 0.25$). The model structure is summarized in Table 1.

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Table 1. Structure of Human Survival State Model

Target Model	Secondary Model	Tertiary Model
Survival State S	Psychological Model X	Psychological Model X1
		Maritime Survival Psychology X2
		Environmental Stress Psychology X3
		Long-term Survival Psychology X4
	Physiological Model L	Injury Model L1
		Hypothermia Model L2
		Disease Model L3
		Food Consumption Model L4
		Water Consumption Model L5
		Energy Expenditure Model L6

Physiological and Psychological Modeling. The physiological state is modeled as:

$$L(t) = \sum w_{li} L_i(t) \tag{5}$$

where submodels capture injury, hypothermia, disease progression, energy depletion, and dehydration. Typical formulations include:

$$L_4(t) = 1 - \frac{E_c(t)}{E_{total}} \tag{6}$$

$$L_5(t) = 1 - \frac{W_{loss}(t)}{W_{crit}} \tag{7}$$

$$L_6(t) = L_0 - k_1 L_1(t) - k_2 L_3(t) - k_3 t \tag{8}$$

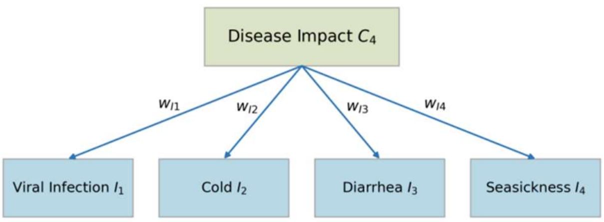

Fig. 2 Structure of disease impact submodel in physiological state assessment.

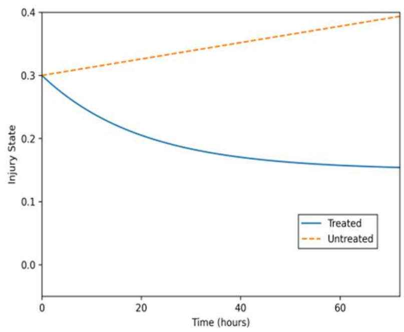

Fig. 3 Evolution of injury state under treated and untreated conditions.

The psychological state is defined as:

$$X(t) = \sum w_{xi} X_i(t) \tag{9}$$

where components represent emergency response, environmental stress, and long-term psychological degradation, typically modeled using exponential decay or piecewise functions.

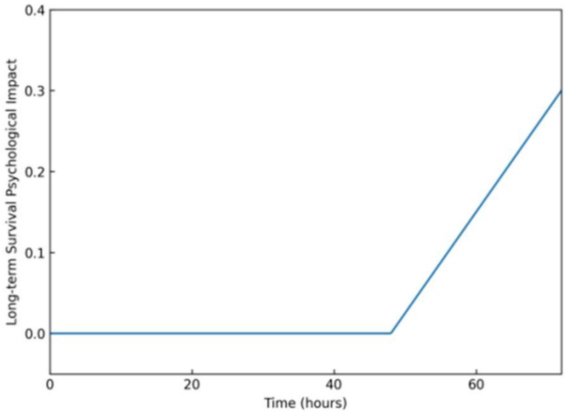

Fig. 4 Long-term psychological degradation during prolonged survival.

4.3. Maritime Survival Environment Model

Environmental effects are represented as a weighted combination of atmospheric and marine factors:

$$H(t) = w_1 TQ(t) + w_2 HJ(t) \tag{10}$$

The structure is summarized in Table 2.

Table 2. Structure of Maritime Environment Model

Target Model	Secondary Model	Tertiary Model
Environment Model H	Natural Weather Model TQ	Ocean Climate Model TQ1
		Rainfall & Solar Exposure Model TQ2
		Severe Weather Model TQ3
	Marine Environment Model HJ	Water Temperature Model HJ1
		Wave Variation Model HJ2
		Current Variation Model HJ3

Each component is defined as:

$$TQ(t) = TQ_1(t) + TQ_2(t) + TQ_3(t) \tag{11}$$

$$HJ(t) = HJ_1(t) + HJ_2(t) + HJ_3(t) \tag{12}$$

where atmospheric factors include climate conditions, rainfall, solar radiation, and extreme weather, while marine factors include water temperature, wave height, and ocean currents. These variables are directly obtained or interpolated from environmental datasets.

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4.4. Model Coupling and Operation

The survival state is computed through dynamic coupling of physiological, psychological, and environmental factors. Interactions among variables are modeled using probabilistic association matrices.

Table 3. Correlation Probabilities Among Physiological Factors

Factor	Fracture	Bleeding	Minor Injury	Cold	Infection	Diarrhea	Seasickness
Fracture	1	0.8	0	0	0.5	0	0
Bleeding	0	1	0	0	0.2	0	0
Minor Injury	0	0.3	1	0	0	0	0
Cold	0	0	0	1	0.2	0.1	0.4
Infection	0	0	0	0	1	0	0.2
Diarrhea	0	0	0	0.3	0	1	0.5
Seasickness	0	0	0	0.2	0	0	1

Table 4. Environmental Impact on Physiological Factors

Factor	Fracture	Bleeding	Minor Injury	Cold	Infection	Diarrhea	Seasickness
Cloudy	0	0	0	0.1	0	0.1	0
Rain	0	0	0	0.3	0	0.2	0
Sun Exposure	0	0	0	0	0	0.1	0.3
Sea State	0	0	0	0.1	0	0	0.2×level

At each time step, environmental conditions update the probability matrices, influencing the evolution of physiological states. The resulting submodel outputs are aggregated to obtain the final survival state $S(t)$.

This time-stepping mechanism enables dynamic multi-factor evaluation under varying environmental conditions.

5. Simulation System Design and Implementation

5.1. System Architecture

To support the integrated application of trajectory prediction and survival state assessment, a maritime survival simulation system is developed based on the proposed framework. The system follows a unified workflow of parameter input, model computation, and result visualization, and adopts a modular and layered architecture to ensure scalability and robustness.

The system is organized into three layers: data layer, model layer, and presentation layer. The data layer manages environmental and individual parameters, including wind, ocean currents, water temperature, and personal attributes such as body weight and physical condition. The model layer integrates the trajectory prediction model and the survival assessment model, serving as the core computational component. The presentation layer provides visualization of simulation results, including trajectory evolution and survival state changes, enabling intuitive interpretation of outputs. This layered design decouples data processing, model computation, and visualization while maintaining coordinated operation through unified interfaces.

Functionally, the system supports trajectory prediction, survival state evaluation, and scenario-based simulation. Given environmental inputs and initial conditions, the trajectory prediction module estimates the position evolution of distressed individuals using a time-stepping

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numerical scheme, while the survival assessment module evaluates physiological and psychological states and integrates them into a unified survival metric through weighted aggregation.

5.2. System Implementation and Operation

During simulation, the trajectory is computed iteratively at each time step using interpolated environmental data, ensuring continuous evolution with low computational cost. The survival assessment is implemented through modular submodels, each representing a specific physiological or psychological factor, and integrated through a unified interface to enhance flexibility and extensibility.

The system supports scenario-driven simulation through flexible parameter configuration. Users can configure environmental and individual conditions to simulate different maritime distress scenarios. Additional parameters, such as water supply or medical assistance assumptions, can also be adjusted for comparative analysis. The corresponding survival state evolution can then be analyzed under different parameter settings.

Simulation results are visualized through an interactive interface for integrated analysis of trajectory evolution and survival dynamics. This facilitates integrated analysis of spatial movement and survival state evolution.

Experimental results demonstrate that the system performs stable trajectory prediction and survival assessment under varying environmental conditions while maintaining computational efficiency. The results exhibit consistent variation trends, reflecting the influence of environmental factors on both trajectory and survival dynamics, indicating that the system provides a practical and extensible platform for maritime survival simulation.

6. Simulation Analysis and Discussion

6.1. Simulation Scenario Setup

To evaluate the effectiveness and stability of the proposed method, comparative simulation experiments are conducted under representative maritime environmental conditions.

In the experimental design, a current-only drifting model is used as a baseline for comparison, while an empirical wind drift model with a constant wind coefficient is introduced as an additional reference. These are compared with the proposed current–wind coupled model. Although more advanced data-driven models exist, simplified baseline models are adopted in this study to ensure controlled comparison and to highlight the effectiveness of the proposed coupling mechanism rather than model complexity.

For the simulation setup, a representative distressed individual is defined using default parameters: a 25-year-old male with a height of 170 cm and weight of 65 kg. The baseline water metabolism rate is set to 60 ml/h, and the physical decline coefficient over 72 hours is set to 0.2. The system incorporates standard basal metabolic rate (BMR) formulations for initializing energy consumption:

$$E_{male} = 66.5 + 13.7W + 5.0H - 6.8A \tag{13}$$

$$E_{female} = 655.1 + 9.56W + 1.85H - 4.86A \tag{14}$$

where W , H , and A denote weight, height, and age, respectively.

The simulation is conducted in a typical offshore region of China, with the initial position set at a longitude of 118.93°E and a latitude of 22.15°N, starting on March 3. Environmental variables, including wind speed, ocean current velocity, and water temperature, are configured based on historical data ranges.

To ensure statistical reliability, each experiment is repeated ten times independently, and the mean values and standard deviations are reported. Due to the limited availability of high-resolution real-world SAR datasets, widely adopted simplified baseline models are used for controlled comparative evaluation. Since publicly available real-world SAR trajectory datasets are limited, the reference trajectories are generated using historical environmental conditions and validated simulation settings commonly adopted in maritime drift studies. The comparative evaluation focuses on relative performance improvement under controlled environmental conditions. All experiments are conducted under the same computational settings to ensure fair comparison.

Although real-world SAR datasets are limited, the simulation settings are derived from empirical maritime studies and calibrated with realistic environmental conditions, ensuring the practical relevance and applicability of the results.

6.2. Drifting Trajectory Simulation Results

Simulation results under varying wind conditions indicate that predicted trajectories are significantly influenced by environmental factors. At low wind speeds, trajectories are primarily governed by ocean currents, resulting in relatively smooth and stable paths. As wind speed increases, trajectories deviate significantly from the current direction and exhibit noticeable lateral dispersion, indicating the perturbation effect of wind forcing. This observation confirms that wind forcing becomes a dominant contributor to trajectory uncertainty under high-wind conditions.

Model performance is evaluated using two standard metrics: Mean Position Error (MPE) and Root Mean Square Error (RMSE). The MPE measures the average Euclidean distance between the predicted and reference positions, which is formulated as:

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left\| P_i^{pred} - P_i^{ref} \right\| \tag{15}$$

where n represents the total number of data points, and P_i^{pred} and P_i^{ref} denote the predicted and reference positions at the i -th time step, respectively. Furthermore, to penalize larger positional deviations more heavily, the RMSE is calculated using the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\| P_i^{pred} - P_i^{ref} \right\|^2} \tag{16}$$

Comparative simulation results show that the proposed model achieves lower MPE and RMSE values than the current-only baseline under the constructed experimental settings. Across multiple trials, the improvement ranges from 8% to 17% across different scenarios, consistent with findings reported in existing maritime drift studies. Additionally, trajectory dispersion and stability metrics are analyzed to evaluate robustness.

Moreover, the joint analysis of trajectory evolution and survival degradation demonstrates the effectiveness of the proposed co-evolution framework in capturing their dynamic interaction, further validating the integrated modeling strategy.

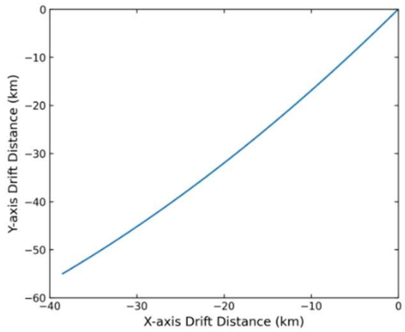

Fig. 5 Simulated trajectory of the distressed individual.

6.3. Survival State Evaluation Results

The survival assessment model is further analyzed by varying key environmental parameters such as water temperature and wind speed.

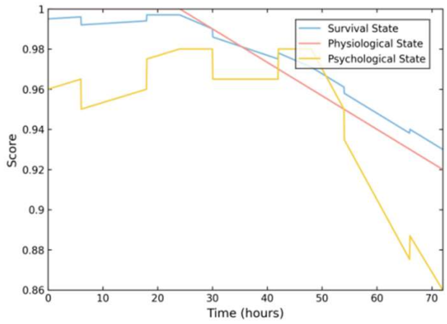

Fig. 6 Evolution of physiological, psychological, and overall survival states over time.

Simulation results indicate that lower water temperatures significantly accelerate heat loss, resulting in a rapid decline in physiological state. In the absence of external supplies, resource depletion-particularly water and energy-becomes the dominant factor affecting survival. Additionally, after approximately 48 hours without rescue, psychological conditions deteriorate sharply, contributing to an overall decline in survival capability.

Model stability is evaluated through repeated simulations under identical conditions, and the standard deviation is calculated as:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - \bar{S})^2} \tag{17}$$

The result yields $\sigma = 0.043$, which is below the stability threshold of 0.05, indicating strong numerical consistency. Furthermore, under ±5% perturbations in environmental parameters, the variation in survival state output remains within 6%, demonstrating good robustness against input uncertainty.

6.4. Effectiveness and Limitations

Overall, the proposed approach is able to capture the influence of environmental factors on both trajectory prediction and survival dynamics. The trajectory model reflects the combined effects of ocean currents and wind forcing, while the survival model provides a dynamic representation of physiological and psychological changes. Their integration offers meaningful support for maritime search and rescue decision-making.

These results indicate that the proposed model effectively captures the coupled effects of environmental and human factors while maintaining reasonable computational efficiency for simulation-based analysis. However, several limitations remain, including the reliance on interpolated environmental data and empirically defined physiological parameters. Future work will incorporate higher-resolution environmental data and real-world rescue records to further improve model fidelity and practical applicability.

The current framework relies on simplified environmental interpolation and empirically defined physiological parameters. In addition, large-scale validation using real-world SAR trajectory datasets has not yet been conducted.

7. Conclusion

A coupled multi-factor framework for maritime survival assessment and drift prediction is proposed. By integrating environmental dynamics with individual physiological and psychological factors, the proposed approach enables unified modeling of trajectory evolution and survival degradation. Experimental results demonstrate improved accuracy, stability, and robustness compared with baseline methods.

The proposed framework enables integrated modeling of environmental dynamics and human survival processes in maritime emergency scenarios, offering potential support for search-and-rescue decision-making and maritime emergency analysis.

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