Dynamic Uncertainty Simulation for Path Optimization Maritime Search and Rescue

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***Abstract*—Maritime search and rescue constitutes a complex multi-variable decision-making problem, where the dynamic drift trajectory of overboard targets is influenced by various uncertain factors including ocean currents, wind forces, and temperature. This paper proposes a maritime rescue path planning decision algorithm based on uncertainty simulation, which achieves real-time optimization of rescue paths by constructing a dynamic drift characteristics model for overboard targets combined with dynamic optimization theory from operations research. Simulation experiments demonstrate that compared to traditional static path planning algorithms, the proposed method significantly improves both rescue success rate and time efficiency.**

Keywords-maritime search and rescue; uncertainty simulation; dynamic optimization; path planning; drift modeling.

I. INTRODUCTION

Maritime Search and Rescue (MSAR) represents a critical component in ensuring the safety of ocean activities, with thousands of maritime distress incidents occurring globally each year[1]. The survival window for overboard individuals is limited, making rapid and accurate rescue path planning directly determinant of rescue success rates. However, the complexity and uncertainty of marine environments pose significant challenges to rescue decision-making.

Traditional rescue path planning predominantly relies on static environmental assumptions, neglecting the dynamic variability characteristics of marine environments. The drift trajectory of overboard targets on the sea surface results from the combined influence of multiple factors including current fields, wind fields, and waves, all of which exhibit notable spatio temporal variability and uncertainty. Furthermore, physiological conditions of overboard individuals, clothing circumstances, and seawater temperature also affect their drift characteristics in water.

Addressing these challenges, this paper proposes an integrated maritime rescue simulation decision framework combining uncertainty modeling with dynamic optimization. By constructing a probabilistic model of dynamic drift for overboard targets and incorporating Markov decision processes with dynamic programming theory, we achieve real-time optimization of rescue paths that accounts for environmental uncertainties.

The remainder of this paper is structured as follows: Section II reviews related work, Section III details problem modeling, Section IV presents the algorithm, Section V discusses simulations, and Section VI concludes.

II. RELATED WORK

Research on maritime rescue path planning has primarily focused on three aspects. Environmental modeling efforts, such as the drift prediction models based on numerical ocean models by Allen et al. [2], often insufficiently account for model uncertainties. Davidson contributed a modified Leeway model through investigating drift characteristics under coupled wind-wave effects. In terms of optimization algorithms, traditional approaches predominantly employ heuristic methods like genetic algorithms and particle swarm optimization to derive optimal search paths [3], while reinforcement learning has recently demonstrated promising potential for dynamic path planning [4]. Regarding uncertainty simulation, some studies utilize Monte Carlo methods to address environmental uncertainties, though at high computational cost [5], and probabilistic graphical models such as Bayesian networks are applied in uncertainty reasoning yet face computational bottlenecks in real-time decision-making [6]. Existing research still exhibits gaps in integrating multi-source uncertainties and real-time dynamic optimization.

III. PROBLEM MODELING

This section establishes the mathematical foundation for representing the drifting targets and rescue vessels under environmental uncertainty, setting the stage for robust path planning.

A. Drift Dynamics Model for Overboard Targets

The motion of overboard targets can be decomposed into active drift and passive drift components[1]. Let the target position at time t be $\mathbf{r}(t)=[x(t),y(t)]^T$, with the dynamic equation:

$$\frac{d\mathbf{r}(t)}{dt}=\mathbf{v}_c(t)+\mathbf{v}_w(t)+\mathbf{v}_d(t)+\boldsymbol{\xi}(t) \ , \quad (1)$$

where $\mathbf{v}_c(t)$ means current velocity, $\mathbf{v}_w(t)$ means wind-induced drift velocity, $\mathbf{v}_d(t)$ means active swimming velocity, $\boldsymbol{\xi}(t)$ means random disturbance term.

B. Uncertainty Modeling

Considering marine environment complexity, each influencing factor exhibits uncertainty. Current uncertainty is modeled using Gaussian random fields, $\mathbf{v}_c(t)\sim\mathcal{N}(\boldsymbol{\mu}_c(t),\Sigma_c(t))$. Wind field uncertainty accounts for random variations in wind speed and direction, $\mathbf{v}_w(t)=f(\mathbf{V}_{wind}(t),\theta(t))$, where wind speed and direction follow joint distributions. Furthermore, the uncertainty in human physiological parameters, such as swimming capability and energy consumption, is modeled as a time-varying stochastic process.

C. Rescue Path Planning Formulation

Define the rescue vessel set as $\mathcal{S}=\{s_1,s_2,\ldots,s_m\}$, with each vessel i at time t having state $\mathbf{x}_i(t)=[x_i(t),y_i(t),v_i(t),\theta_i(t)]^T$, including position, velocity and heading. The rescue path planning objective minimizes expected rescue time:

$$\min_\pi \mathbb{E}[T_{rescue}(\pi)]=\min_\pi \mathbb{E}\left[\min_{i\in\mathcal{S}} T_i^{arrival}\right] \quad (2)$$

Constraints include vessel dynamics, collision avoidance, fuel consumption.

IV. Dynamic Optimization Algorithm Design

This section presents a real-time decision-making framework that integrates forecasting, uncertainty propagation, and iterative optimization to adaptively plan rescue paths.

A. Receding Horizon Optimization Strategy

Formulate the rescue path planning as a Partially Observable Markov Decision Process (POMDP). Adopt a Model Predictive Control (MPC) framework, solving finite-horizon optimization at each decision epoch:

$$\pi^*(t)=\arg\min_\pi \sum_{\tau=t}^{t+H}\mathbb{E}[R(x_\tau,u_\tau)] \ , \quad (3)$$

where H is the prediction horizon length. Real-time path adjustment through receding horizon optimization accommodates dynamic environmental changes.

B. Uncertainty Propagation and Bayesian Update

Employ particle filtering for state estimation and uncertainty propagation. Predict next-state distribution using dynamics model and current particle distribution. Incorporate observation information to update posterior distribution via Bayes' theorem. Prevent particle degeneracy and maintain particle diversity.

V. Simulation Experiment Design

We build a simulation environment based on real ocean data. HYCOM (Hybrid Coordinate Ocean Model) provides global ocean current reanalysis data at a spatial resolution of 1/12° . ECMWF ERA5 offers meteorological reanalysis wind data with a temporal resolution of one hour. Significant wave height and wave period data are sourced from the Wave Watch III model.

Design three typical rescue scenarios, including nearshore rescue, open-ocean rescue and beyond 50 nautical miles offshore. Compare the proposed dynamic optimization algorithm against baseline methods: Greedy algorithm: Each vessel selects nearest target. Static A* algorithm: Plans shortest path based on current environment state. Genetic algorithm: Heuristic method for global optimization. Reinforcement learning: End-to-end Deep Q-Network based approach.

In an academic research setting, our method benefits from high-performance computing resources, including multi-core CPUs, large RAM (⩾ 256GB), and high-end GPUs (e.g., NVIDIA A100), which support rapid iteration and model development through distributed deep learning frameworks such as PyTorch. For practical real-time deployment, however, we emphasize a cloud-edge architecture. Optimized models can be deployed on low-power edge devices (e.g., NVIDIA Jetson Orin) for millisecond-level inference, while cloud-based GPUs facilitate periodic retraining. This balance ensures scalability and responsiveness in harsh maritime environments.

VI. Conclusion and Future Work

This paper proposes a dynamic optimization algorithm for maritime rescue path planning based on uncertainty simulation, with main contributions. Developed comprehensive multi-source uncertainty drift model improving drift prediction accuracy. Designed Markov decision process-based dynamic optimization framework enabling real-time path adjustment. Implemented particle filtering for uncertainty propagation effectively handling high-dimensional uncertainties. Validated algorithm efficacy through large-scale simulations demonstrating significant improvements over traditional methods.

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