# Dynamic Uncertainty Simulation for Path Optimization Maritime Search and Rescue

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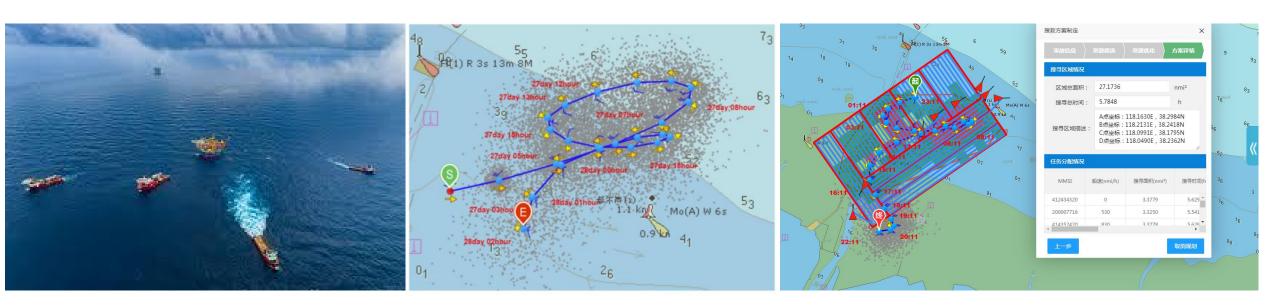
Research Interests: Humanitarian rescue planning, Learning-based optimization

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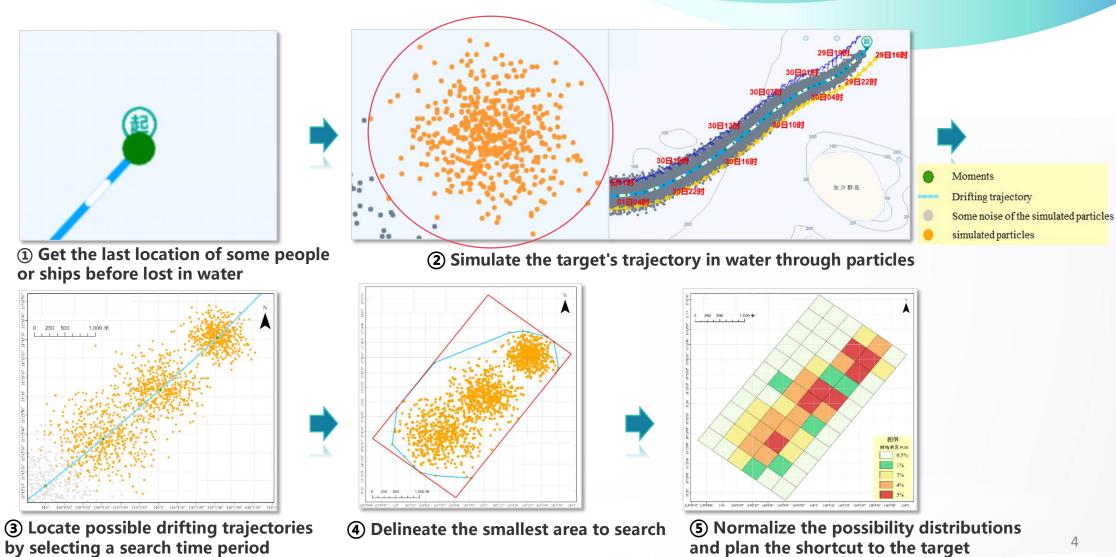
### **Background: Maritime Search and Rescue (MSAR)**

- MSAR remains a major challenge despite maritime tech advancements.
- Major disasters (MH370, Air France 447) highlight MSAR inadequacies, causing tragic loss of lives.
- Many overboard individuals become missing or deceased due to prolonged search times.





# **Background & dataset**





#### **Problem Formulation**

#### A. Drift Dynamics Model for Overboard Targets

■ The motion of overboard targets can be decomposed into active drift and passive drift components:

$$\mathbf{r}(t) = [x(t), y(t)]^T$$

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

### **B.** Uncertainty Modeling

■ Current uncertainty is modeled using Gaussian random fields:

$$\mathbf{v}_c(t) \sim \mathcal{N}(\mathbf{\mu}_c(t), \Sigma_c(t))$$

■ Wind field uncertainty accounts for random variations in wind speed and direction:

$$\mathbf{v}_{w}(t) = f(\mathbf{V}_{wind}(t), \theta(t))$$



#### **Problem Formulation**

### C. Rescue Path Planning Formulation

- Define the rescue vessel set as:  $S = \{s_1, s_2, ..., s_m\}$
- **■** Each vessel at time having state, including position, velocity and heading:

$$\mathbf{x}_{i}(t) = \left[x_{i}(t), y_{i}(t), v_{i}(t), \theta_{i}(t)\right]^{T}$$

■ The rescue path planning objective minimizes expected rescue time:

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

Constraints include vessel dynamics, collision avoidance, fuel consumption.



#### **Optimization Algorithm Design**

### 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:

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

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



#### **Optimization Algorithm Design**

# **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.



#### **Conclusion and Future Work**

- Key contributions include:
- 1) This paper proposes a dynamic optimization algorithm for maritime rescue path planning based on uncertainty simulation, with main contributions.
- 2) Developed comprehensive multi-source uncertainty drift model improving drift prediction accuracy.
- 3) Designed Markov decision process-based dynamic optimization framework enabling real-time path adjustment.
- **■** Future research directions include:
- 1) Integration of real-time sensor data for online model adaptation.



# **THANKS**