UACOF: A USV-AUV Collaboration Framework for Underwater Tasks under Extreme Sea Conditions (Student Abstract)

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Abstract

Ocean exploration requires effective collaboration between the unmanned surface vehicle (USV) and autonomous underwater vehicles (AUVs). We propose UACOF, a USV-AUV collaboration framework that enhances multi-AUV performance under extreme sea conditions. The framework includes high-precision multi-AUV location via USV path planning with Fisher information matrix optimization and reinforcement learning training for cooperative tasks. Experimental results show UACOF's superior feasibility, performance, coordination and robustness in extreme conditions.

Introduction

Autonomous underwater vehicles (AUVs) are valuable for ocean exploration due to their flexibility and ability to carry communication and detection units (Hou et al. 2023; Fang et al. 2022; Wu, Low, and Lv 2020; Jiang et al. 2024). Nevertheless, AUVs alone often face challenges such as accurate positioning and intelligent swarm control in harsh and extreme sea conditions (Xu et al. 2024; Du et al. 2023; Zhang et al. 2023; Bahr, Leonard, and Martinoli 2012). To address the aforementioned challenges, researchers have concentrated on the development of unmanned surface vehicle (USV)-AUV co-localization and intelligent multi-AUV collaboration (Wang et al. 2024, 2023; Hu et al. 2021).

Based on the above intuition, in this study we propose UACOF, a **U**SV-**A**UV **co**llaboration **f**ramework for underwater tasks to improve the performance of the AUV completing tasks under extreme sea conditions. To make a conclusion,the contributions of this paper include the following:

- We achieve accurate AUV positioning using USV path planning by minimizing the Fisher information matrix (FIM) determinant. Integrating environment awareness into the state space and USV-AUV collaboration into the reward function, we further use reinforcement learning (RL) to enhance multi-AUV intelligence and adaptability to the extreme sea conditions.
- We innovatively leverage shallow water equations and ocean turbulence model to simulate the extreme sea conditions. Through comprehensive experiments in the data collection task, our framework showcases superior feasibility and excellent performance in balancing multi-objective optimization under extreme sea conditions.

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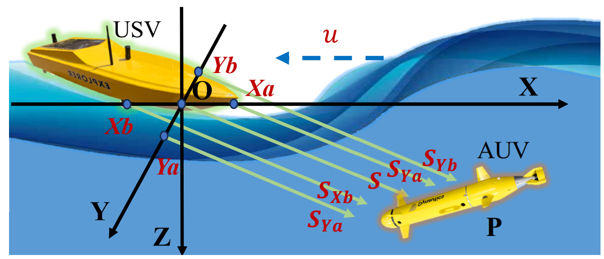

Figure 1: Illustration of the AUV positioning via USV. The USV on the seasurface uses USBL to locate the AUV.

Methodology

USV Path Planning Based on FIM Optimization. The UACOF framework achieves accurate AUV positioning through USV path planning by minimizing the system's FIM determinant,which is inversely related to system uncertainty.

The USV at coordinates (x, y, η) uses a USBL system to locate the k-th AUV at (x_k, y_k, z_k). Arrays on the USV are spaced uniformly with distances $OXa = OXb = OYb = OYa = d/2$. The probability density function and measurement equation of the data are then derived as follows:

$$p(\boldsymbol{Z},\boldsymbol{X})=\prod_{k=1}^{m}\frac{\exp\left\{-\frac{1}{2}[\boldsymbol{Z}_k-\boldsymbol{h}_k(\boldsymbol{X})]^T\boldsymbol{R}^{-1}[\boldsymbol{Z}_k-\boldsymbol{h}_k(\boldsymbol{X})]\right\}}{\sqrt{2\pi\det(\boldsymbol{R})}}, \quad (1a)$$

$$\boldsymbol{Z}_k = \boldsymbol{h}_k(\boldsymbol{X}) + \boldsymbol{u}_k, \quad (1b)$$

$$S_k = \sqrt{(x_k - x)^2 + (y_k - y)^2 + z_k^2}, \quad (1c)$$

where $\boldsymbol{X} = [x, y]^T$ denotes the target state vector, while $\boldsymbol{h}_k(\boldsymbol{X}) = [\Delta\varphi_{x,k}, \Delta\varphi_{y,k}]^T$ represents the phase difference vector, including $\Delta\varphi_{x,k} = \frac{2\pi f d}{cS_k}(x_k - x)$ and $\Delta\varphi_{y,k} = \frac{2\pi f d}{cS_k}(y_k - y)$. Here, c represents the sound speed, f is the signal frequency, and $\boldsymbol{u}_k$ denotes zero-mean Gaussian white noise with measurement noise covariance matrix $\boldsymbol{R}=\sigma^2\boldsymbol{I}$.

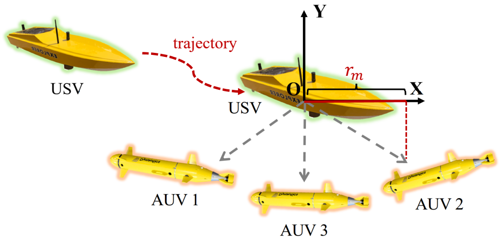

Figure 2: The diagram of USV path planning. We can realize accurate positioning of AUVs via USV path planning through minimizing the determinant of the system's FIM.

Assume there are totally m AUVs, then FIM of the system is subsequently obtained by determining the second derivative of the log-likelihood function, the determinant of the FIM can be simplified to the final expression after derivation, which can be expressed as follows

$$\boldsymbol{J}_m = \begin{bmatrix} -E\left[\frac{\partial^2 \ln p(\boldsymbol{Z},\boldsymbol{X})}{\partial x^2}\right] & -E\left[\frac{\partial^2 \ln p(\boldsymbol{Z},\boldsymbol{X})}{\partial x \partial y}\right] \\ -E\left[\frac{\partial^2 \ln p(\boldsymbol{Z},\boldsymbol{X})}{\partial y \partial x}\right] & -E\left[\frac{\partial^2 \ln p(\boldsymbol{Z},\boldsymbol{X})}{\partial y^2}\right] \end{bmatrix}, \tag{2a}$$

$$\det(\boldsymbol{J}_m) = \left(\frac{4\pi^2 f^2 d^2}{\sigma^2 c^2}\right)^2 \left[3m \frac{\sin^2\gamma_0}{S_0^4} + \frac{\left(\sin^4\gamma_0 + 1\right)^2}{S_0^4}\chi\right], \tag{2b}$$

$$r_m = \operatorname{argmax}\left\{\det\left(\boldsymbol{J}_{\mathrm{m}}\right)\right\}, \tag{2c}$$

where $\sin\gamma_0 = \frac{z_k}{S_0}$, while $\chi = \sum_{1 \le i < j \le m}^{m} \sin^2\alpha_{ij}$, with $\alpha_{ij} = \varphi_i - \varphi_j$ representing the angle between the projections of two AUVs and USV. By maximizing the determinant $\det(\boldsymbol{J}_m)$, we can determine the optimal horizontal distance r_m between USV and multiple AUVs, as illustrated in Figure 2.

Reinforcement Learning Enabled Multi-AUV Collaboration. Our UACOF framework leverages RL to train multiple AUVs for collaborative operations. We modify standard MDP-based RL algorithms by adjusting the state space and reward functions. Specifically, we include the ocean current velocity perceived by AUV k into its state space:

$$s_k = \left\| \boldsymbol{V}_c\left(\boldsymbol{P}_k(t)\right) \right\|. \tag{3}$$

Furthermore, we combine the original reward functions with the distance differential between each AUV and the USV, which can be denoted as

$$r_k(t) = \left(l_{\max}^{k \leftrightarrow U} / l^{k \leftrightarrow U}(t)\right), \tag{4}$$

where $l_{\max}^{k \leftrightarrow U}$ and $l^{k \leftrightarrow U}$ represent the maximum and current distances between AUV k and USV, respectively. With extensive RL training, the multi-AUV system's collaborative behavior and decision-making, enhanced by environment-awareness, will converge to an expert level.

Simulation Experiments

Since open-source underwater tasks are scarce, we use a underwater data collection task to evaluate the USV-AUV collaboration framework's performance. For more details and parameters, refer to the previous work (Zhang et al. 2024).

To evaluate UACOF framework's feasibility, we used DDPG and SAC to train two AUVs, positioned by a USV,

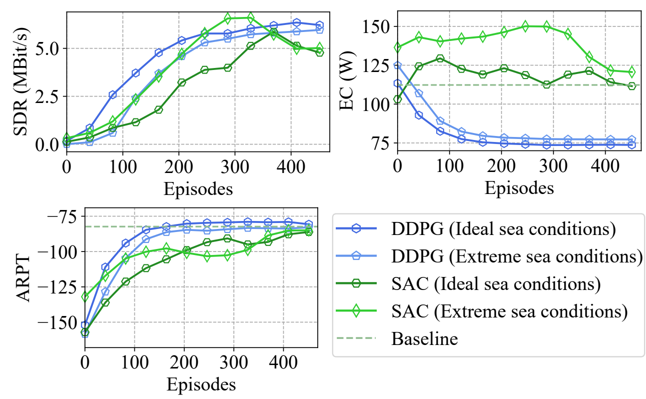

Figure 3: The curves of sum data rate (SDR), energy consumption (EC) and average reward per timestep (ARPT), using DDPG and SAC for RL training under ideal and extreme sea conditions, respectively.

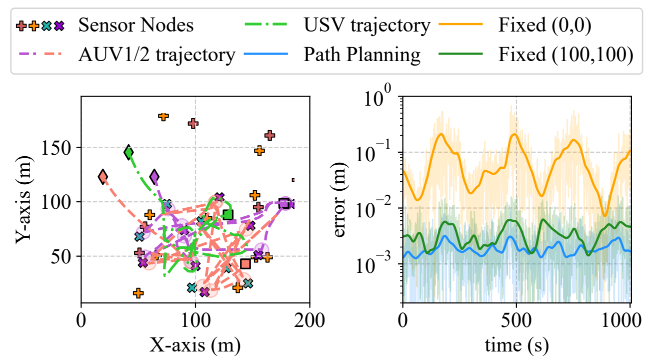

Figure 4: Trajectories of AUVs and USV, and positioning error of the AUV with USV fixed at (0,0) and (100, 100), and path planning using FIM optimization, respectively.

to complete the task under both ideal and extreme sea conditions. As shown in Figure 3, training curves converge to expert-level performance, indicating successful acquisition of the expert policy through RL training. Environmental generalization experiments comparing ideal and extreme conditions show that performance metrics remain comparable despite ocean waves and turbulence. This demonstrates the framework's robustness under extreme conditions.

We used a DDPG-trained expert policy to guide the multi-AUV system in underwater data collection under extreme sea conditions. Figure 4(a) shows the AUVs and USV trajectories during a training episode. To evaluate the USV-AUV collaboration framework, we analyzed positioning errors in three scenarios: USV path planning with FIM optimization, USV fixed at (0,0), and USV fixed at (100,100). Figure 4(b) indicates that the FIM-optimized path planning approach achieves the lowest positioning error, demonstrating superior positioning performance under extreme conditions.

Finally, given the limited space, we have made the codes and supplementary materials available as open-source at https://github.com/360ZMEM/USV-AUV-colab.

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Ethical Statement

This paper presents work whose goal is to explore using the USV-AUV collaboration framework to improve the performance for underwater tasks under extreme sea conditions. There are many potential societal consequences of our work, none of which we feel must be specifically highlighted here.

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