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Cooperative tracking of multiple targets underwater by multiple autonomous underwater vehicles (AUVs) multi-agent reinforcement learning

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Introduction

Advancements in underwater technology have popularized the use of AUV swarms for ocean exploration and surveillance. Despite challenges in tracking targets in complex environments, this paper presents a cooperative multi-AUV tracking algorithm that incorporates real underwater dynamics. We utilize a Multi-Agent Reinforcement Learning (MARL) framework enhanced by Software-Defined Networking (SDN) to improve flexibility and scalability [1]. New techniques like "dynamic-attention switching" and "dynamic-resampling switching" enhance efficiency and accuracy. We also introduce a new classification method and the ASMA tracking algorithm, which significantly outperforms existing solutions in convergence speed and precision.

Results & Discussion 2

We introduce a dynamic multi-agent reinforcement learning framework for AUV swarms to track multiple targets underwater, incorporating underwater sonar and ocean current modeling. Our novel MARL architecture, FATHOM-Net, based on SDN, enhances the AUV swarm's flexibility and robustness. The system includes "dynamic-switching attention" and "resampling" mechanisms to boost learning efficiency and accuracy. We also develop ASMA, an algorithm using fuzzy logic and expert systems to effectively classify AUV formations amid ocean currents, improving tracking performance.

Experiments & Methodology

Sonar Detection Modeling 1.1

Sonar technology is used for tracking AUVs in challenging underwater environments due to the limitations of electromagnetic detection.

Ocean current modeling 1.2

$$\rho\left(\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u}\right) = -\nabla p + \mu \nabla^2 \mathbf{u} + \mathbf{E}$$

Linearized Navier-Stokes Equation:

$$o \frac{\partial \mathbf{u}}{\partial t} = -\nabla p + \mu \nabla^2 \mathbf{u} + \mathbf{F}$$

Simplifies Navier-Stokes by assuming laminar flow and neglecting nonlinear terms.

Drag Equation:

$$F_D = \frac{1}{2}\rho C_D u^2 A$$

Calculates drag force based on fluid density, velocity, drag coefficient, and frontal area.

Lift Equation:

$$F_L = \frac{1}{2}\rho C_L u^2 A$$

Computes lift force using fluid density, velocity, lift coefficient, and frontal area.

Virtual Mass Equation:

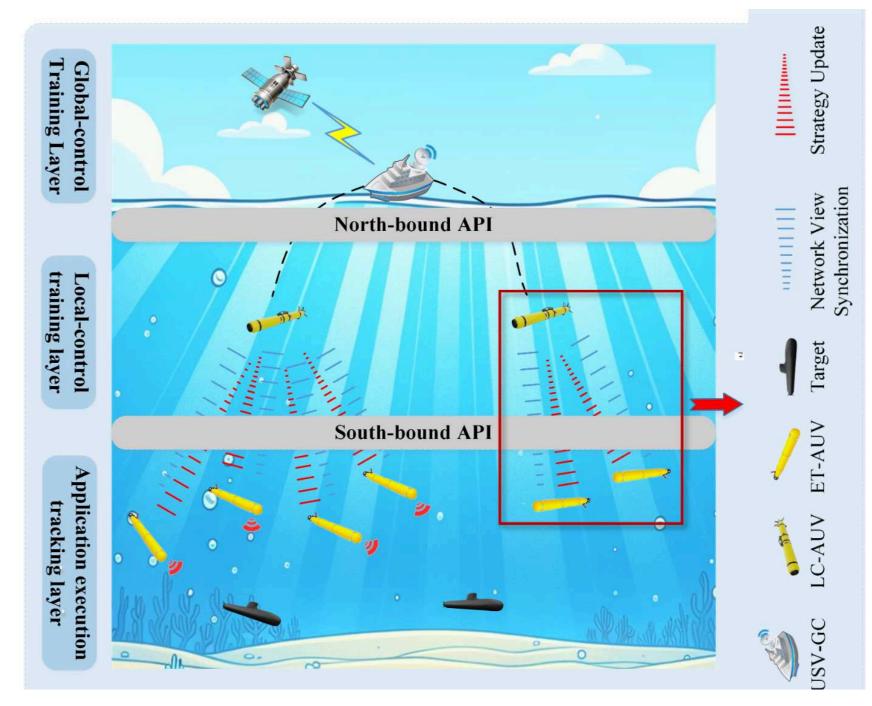
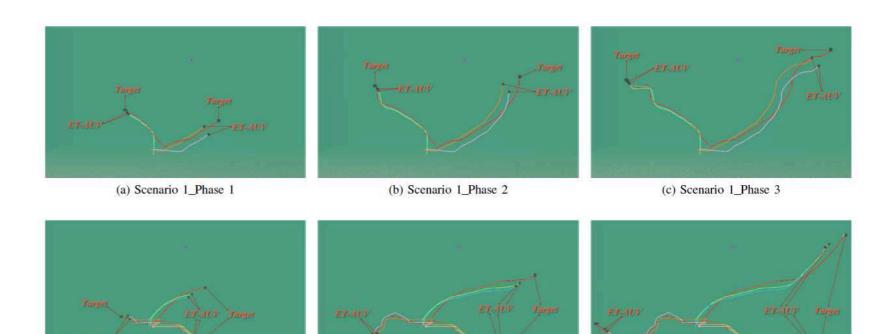


Figure 2: Task classification and Proposed methodology of FATHOM-Net



$$F_{VM} = mC_{VM}\frac{\partial \mathbf{u}}{\partial t}$$

Calculates resistance from fluid mass displaced by an object's acceleration.

Markov decision process modeling 1.3

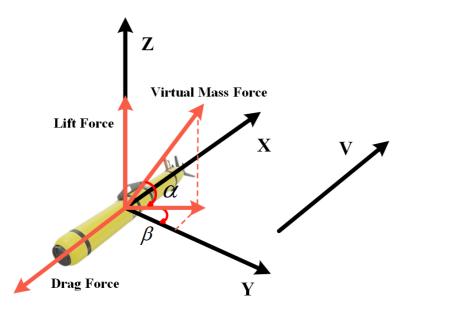


Figure 1: Schematic diagram of ocean current

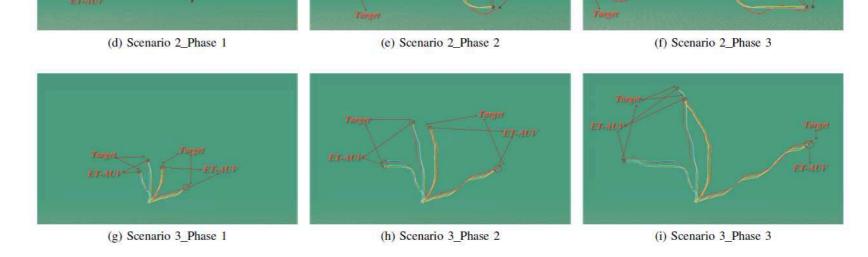


Figure 3: Test for the availability of the proposed approaches in 3D environment

References

[1] Shengbo Wang, Chuan Lin, Guangjie Han, Shengchao Zhu, Zhixian Li, and Zhenyu Wang. Multi-auv cooperative underwater multi-target tracking based on dynamic-switching-enabled multi-agent reinforcement learning. arXiv preprint arXiv:2404.13654, 2024.