Learning-based Integrated Cooperative Motion Planning and Control of Multi-AUVs ⋆

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Abstract: This paper introduces a learning-based solution tailored for the integrated motion planning and control of Multiple Autonomous Underwater Vehicles (AUVs). Tackling the complexities of cooperative motion planning, encompassing tasks such as waypoint tracking and self/obstacle collision avoidance, becomes challenging in a rule-based algorithmic paradigm due to the diverse and unpredictable situations encountered, necessitating a proliferation of if-then conditions in the implementation. Recognizing the limitations of traditional approaches that are heavily dependent on models and geometry of the system, our solution offers an innovative paradigm shift. This study proposes an integrated motion planning and control strategy that leverages sensor and navigation outputs to generate longitudinal and lateral control outputs dynamically. At the heart of this cutting-edge methodology lies a continuous action Deep Reinforcement Learning (DRL) framework, specifically based on the Twin Delayed Deep Deterministic Policy Gradient (TD3). This algorithm surpasses traditional limitations by embodying an elaborated reward function, enabling the seamless execution of control actions essential for maneuvering multiple AUVs. Through simulation tests under both nominal and perturbed conditions, considering obstacles and underwater current disturbances, the obtained results demonstrate the feasibility and robustness of the proposed technique.

Keywords: Integrated motion planning and control, cooperative motion, machine learning, autonomous underwater vehicle, DRL.

1. INTRODUCTION

Autonomous underwater vehicles (AUVs) are unmanned and self-driving vehicles that enhance the collection of oceanic data. Their applications include determining the physical and chemical qualities of water, exploring and mapping the seabed, conducting search and rescue operations, and inspecting pipelines in the oil and gas industry (Wang et al. (2023a); Hadi et al. (2021)). There is an increasing trend towards utilizing groups of AUVs (Wang et al. (2023b); Lechene et al. (2024)), driven by the need to conduct complex missions, such as disaster recovery. The simultaneous utilization of multiple vehicles can potentially capture more extensive data, shorten mission time, increase the chance of success, and improve safety in achieving the intended objective. Motion planning is the systematic procedure of identifying a feasible path between two points of departure and arrival that bypasses all obstacles. This is achieved by taking into account various factors such as the distance covered, smoothness of the path, control effort, anticipated arrival time, environmental uncertainties, and more (Hadi et al. (2021)). Several techniques employed in the motion planning of multiple AUVs include artificial neural networks (Huang et al. (2016)), optimal control methods (Zhuang et al. (2019)), evolutionary algorithms (Xiong et al. (2019)), and artificial potential fields (Fiorelli et al. (2006)). Given the unknown and undiscovered nature of the environment in which AUVs operate, the suggested methodologies still need enhancement to effectively deal with environmental disturbances and control group mobility. Hence, employing Artificial Intelligence (AI) techniques can be a progressive approach to planning the navigation of AUVs and developing intelligent autonomous systems capable of making informed decisions (Hadi et al. (2021)). Reinforcement learning is an AI strategy that is suitable for dealing with complex challenges and unpredictable situations in autonomous systems. It is a biologically inspired method combining the concept of experience-based learning with the reward and punishment principle (Buşoniu et al. (2018)).

Recent studies reveal a growing tendency in the application of DRL approaches in marine systems (Sarhadi et al. (2022); Er et al. (2024); Chaffre et al. (2023)). As some notable examples, Sun et al. (2019) propose end-to-end motion planning for an under-actuated AUV. The approach uses sensor inputs to adjust the AUV's surge force and yaw moment. The proximal policy optimization algorithm finds optimal paths. Bhopale et al. (2019) described

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a modified Q-learning approach to prevent AUVs from colliding with obstacles. In this strategy, the researchers created a hazard zone near obstacles to reduce the likelihood of a collision. When the AUV enters the danger zone, exploration stops, and exploitation continues until the danger zone is exited. Hadi et al. (2022) employ deep reinforcement learning for adaptive path planning and control of a 6-DOF REMUS AUV. The AUV's control is achieved by regulating the rudder fin at a constant speed. Wang et al. (2018) developed the RL algorithm for guiding multiple AUVs in information collection tasks in a limited continuous space. Hadi et al. (2023) deploy a distributed DRL approach for motion planning and obstacle avoidance for multiple AUV formations. A binocular-vision-based motion planning is proposed by (Yan et al. (2023)) for an AUV. In Hasankhani et al. (2023) an integrated path planning and tracking framework is developed for turbines acting as fully autonomous underactuated energy harvesting AUVs based on the proximal policy optimisation (PPO) method is developed in (Hasankhani et al. (2023)). They used two PPO networks to achieve their path planning and tracking objectives. The PPo-based tracking network receives the output of PPo-based path planning, along with sensor data, and generates actuator commands for the AUV. Havenstrøm et al. (2021) proposes employing DRL techniques to construct autonomous agents capable of achieving the hybrid aim of following a path while avoiding collisions. The goal is to create autonomous vehicle systems as intelligent as humans. The agent is trained using a curriculum-based learning approach in which the difficulty of the tasks is progressively increased. The DRL agent issued the commands for three signals: propeller propulsion, elevator fin, and rudder. A PI controller maintained the cruise speed while the DRL agent actuated the control fins. The research Chu et al. (2023) examines the problem of path planning for an AUV in the presence of disturbances caused by ocean currents. The DRL path planning method employs a double-deep Q network (DDQN). Using a dynamic and composite reward function, the AUV can navigate obstacles and successfully reach its target destination.

In general, there are two paradigms in decision-making and control system design for autonomous vehicles. The first one involves rule-based algorithms, which usually utilize the model or geometry of vehicles in design. These algorithms are robust and commonly used; however, in complicated missions, they become cumbersome to code and test. The second paradigm applies learning-based algorithms in the category of AI and reinforcement learning. Although they seem to be simpler, their applications are yet to emerge. Therefore, developing new schemes that can learn and generalize their knowledge in complicated scenarios is important. The contribution of this paper is to introduce a novel paradigm in the second category that performs integrated planning and control for the cooperative motion of multi-AUVs. The proposed algorithm uses navigation data to generate control signals and can potentially replace conventional guidance and control algorithms, which are common in the first paradigm.

The rest of this paper is organized as follows: the concepts of cooperative motion planning are defined in Section 2. Section 3 describes our suggested strategy, incorporating the proposed algorithm alongside the states, actions, and reward function components of the DRL algorithm. Section 4 presents simulation results for two scenarios. Finally, Section 5 provides the conclusions.

2. COOPERATIVE MOTION PLANNING MISSION

The underwater environment is constantly changing, with limitations on data transmission, power, and sensing technology. Path planning algorithms assume knowledge of the surrounding underwater environment, but it is important to note that this environment is highly dynamic and unpredictable (Wang et al. (2023a)). When navigating AUVs through complex ocean environments with high levels of uncertainty, safety should be the top priority in path planning execution. In this context, safety can be considered as the lack of risk in terms of collisions and maintaining reliability in algorithms. Hence, investigating algorithms like the one developed in this paper is of interest. In cooperative motion, the goal for the vehicles is to work together and locate one or various targets by following an optimized path. As depicted in Figure 1, AUVs are primarily tasked with efficiently navigating towards designated points while ensuring the safe avoidance of static and dynamic obstacles (other AUVs). To achieve this goal, AUVs are initially placed in random positions within a specified geographical area, and obstacles within their movement space are also randomly defined. Similarly, targets can be non-identical and selected randomly within a designated region.

Classical algorithms incorporate two separate motion planning (guidance) and control algorithms to accomplish this task Hadi et al. (2021). In this paper, a learning-based integrated planning and control approach is proposed, as illustrated in Fig. 2. Trained algorithms in AUVs receive sensing and navigation information (states) and generate necessary control signals (actions) for target tracking and collision avoidance.

In the training phase for the algorithms, a nonlinear model of AUVs is exploited, which is briefly discussed here. The model consists of 3 Degrees Of Freedom (3DOF) in motion. It is assumed that the AUVs are controlled at a constant

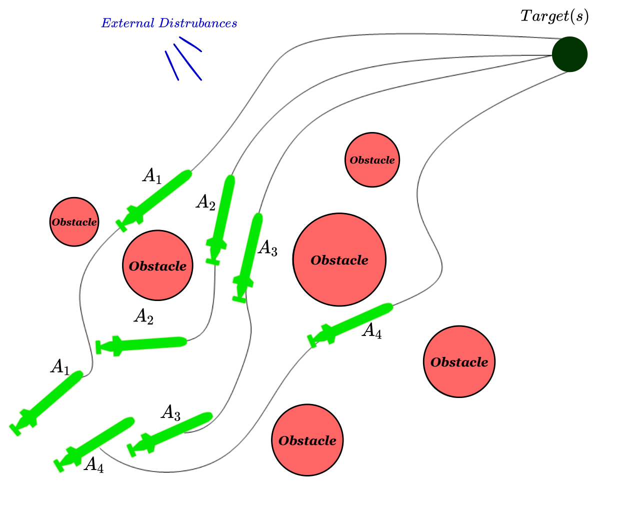

Fig. 1. The proposed integrated motion planning and control block-diagram

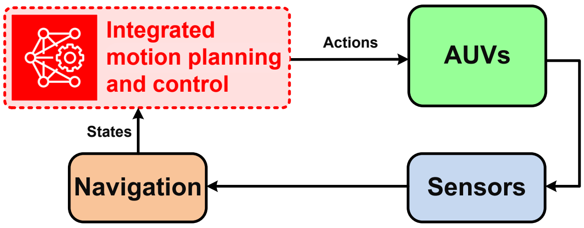

Fig. 2. Diagram of AUV motion planning based on the proposed approach

depth. The mathematical model for AUVs, neglecting heave, roll, and pitch motions, can be described as follows (Fossen (2011)):

$$\dot{\eta} = J(\eta)\nu \tag{1}$$

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau + \tau_d \tag{2}$$

The AUV's location in the earth-fixed frame is denoted by the position vector $\eta = [x \ y \ \psi]^T$, which includes the (x, y) coordinates and ψ the yaw angle. Expressing the AUV's motion in the body-fixed frame, the velocity vector is denoted as $\nu = [u \ v \ r]^T$, where u represents surge velocity, v stands for sway velocity, and r symbolizes the yaw rate. The rotation matrix $J(\psi) \in \mathbb{R}^{3\times3}$ is used to rotate the AUV's velocity vector from the body-fixed frame to the earth-fixed frame. In this equation, M represents the positive definite mass matrix, while the Coriolis terms and centripetal force matrix are denoted by $C(\nu)$. Moreover, the damping matrix is denoted by $D(\nu)$. The input control vector comprises the surge force and the yaw moment, $\tau = [\tau_u, 0, \tau_r]$. Additionally, τ_d represents a disturbance that can model underwater ocean currents. One can refer to Fossen (2011) for further details about the exploited model and parameters of the vehicle Cui et al. (2010).

3. THE PROPOSED APPROACH

In this paper, a DRL algorithm is developed to learn and execute the integrated planning and control task discussed in the previous section. DRL algorithms with actor-critic structures are effective in controlling systems that are not fully determined, and known for their optimality and adaptability. Leveraging its successful history in continuous control, the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm is employed to accomplish the task. In general, reinforcement learning is a type of machine learning in which an agent interacts with the environment by taking actions, receiving rewards, and refining its approach over time Sutton et al. (2018). The main goal is to create a data-driven decision-making system capable of making optimal decisions by maximizing the expected return, which is the sum of future rewards, as follows: This process helps the agent to improve its decision-making skills gradually. (Sutton et al. (2018))

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+(k+1)} \tag{3}$$

where γ is the discount factor that falls within the range $[0, 1]$ and influences the present value of future rewards. The reward function is the objective of quantifying the immediate feedback or desirability associated with an agent's action in a given state. Starting from the state s and following the policy π accordingly, the discounted expected state-value function is defined as:

$$V^\pi(s) = E_\pi\left[R_t \mid s_t = s\right] = E_\pi\left[\sum_{k=0}^{\infty} \gamma^k r_{t+(k+1)} \mid s_t = s\right] \tag{4}$$

and, under the policy π, the action-value function represents the value of action a in the state s as follows:

$$\begin{aligned} Q^\pi(s,a) &= E_\pi[R_t \mid s_t = s, a_t = a] \\ &= E_\pi\left[\sum_{k=0}^{\infty} \gamma^k r_{t+(k+1)} \mid s_t = s, a_t = a\right] \end{aligned} \tag{5}$$

The Bellman Optimality Equations are defined as follows:

$$V^*(s) = \max_a E\left[r_{t+1} + \gamma V^*\left(s_{t+1}\right) \mid s_t = s, a_t = a\right] \tag{6}$$

$$Q^*(s,a) = E\left[r_{t+1} + \gamma \max_a^* \left(s_{t+1}, a'\right) \mid s_t = s, a_t = a\right] \tag{7}$$

where $V^*(s) = \max_a Q^*(s,a)$ for all the states. Actor-critic methods often suffer from the problem of overestimation. Research has shown that discrete actions are not effective in such settings. The implications of this are clear: reducing overestimation can have a significant impact on the performance of modern algorithms. To better understand the relationship between noise and overestimation, researchers have examined the accumulation of errors that result from temporal difference learning. This highlights the significance of standard methods in deep reinforcement learning, and target networks and investigates their role in limiting errors from imprecise approximation and stochastic optimization. The SARSA style regularization method was introduced for this purpose. From these developments emerged the TD3 algorithm. This is a model-free, online, off-policy reinforcement learning approach that is specifically designed to work in continuous action spaces (Fujimoto et al. (2018)). In this study, using TD3, AUVs can reach their intended destinations without colliding with obstacles or other AUVs. The following sections will present the states, actions, and reward functions for this approach.

States and actions. The objective of every AUV is to reach its intended location by choosing the most direct route. Therefore, the state space is determined by the AUV's directional deviation from its objective and its proximity to any identified obstacles.

$$S_{\mathrm{AUV}_i} = \left[e_{Ai}, \frac{d_{\mathrm{Aj}} - \mathrm{r}_{\mathrm{det_i}}}{r_{\mathrm{det_i}}}\right], \mathrm{i} = 1,2,3,4, \mathrm{j} = O, \ \mathrm{A} \tag{8}$$

$$\frac{d_{\mathrm{Aj}} - r_{\mathrm{det_i}}}{r_{\mathrm{det_i}}} = \begin{cases} \text{value} & \text{if sensors detect obstacle} \\ 0 & \text{else} \end{cases}$$

The AUV's direction error towards the target is given by $e_{Ai} = \lambda_i - \psi_i$, where λ_i represents the direction of the target and ψ_i is the heading angle of each AUV. The $N\times1$ vector d_{Aj} represents the distance of the i-th AUV to recognized obstacles or other AUVs, where N is the total number of objects (AUV and obstacle). The maximum detection range of the AUV sensor is denoted by a scalar r_{det}. The letters A and O are abbreviations for AUV and obstacles, respectively.

To make the AUV reach its desired destination, it is important to control the speed and direction. This is done by controlling the surge force τ_u and the yaw moment τ_r.

$$a = [\tau_u, \tau_r] \tag{9}$$

Reward function. The proposed algorithm utilizes a reward function to encourage desired behavior and discourage undesired actions. The objective is to find the most efficient routes to track waypoints while avoiding potential collisions. For this purpose, three main components are considered, which are explained below:

Target reward (r_1) This reward function ensures that the AUV reaches its intended location.

$$r_1 = -|\lambda - \psi| \tag{10}$$

Obstacle avoidance (r_2) To help AUVs avoid obstacles and collisions, this study presents the reward function, which is defined as follows:

$$r_2 = \sum_{i=1}^{\ell} r_i, \qquad r_i = \begin{cases} 0 & \text{if } d_{AO} > d_{\text{avoid}} \\ -\left|d_{\text{avoid}} - d_{AO}\right| & \text{otherwise} \end{cases} \tag{11}$$

Here, ℓ represents the number of obstacles detected by the AUV's sensors. The distance between the AUV and an obstacle, denoted as d_{AO}, is another parameter. Additionally, $d_{\text{avoid}} = r_A + d_L + r_{\text{obs}}$, where r_A stands for the radius of the shell assumed around the AUV, d_L represents the safe distance from the shell of an AUV, and r_{obs} signifies the radius of the obstacle.

Self-collision avoidance reward (r_3) As defined below:

$$r_3 = \begin{cases} 0 & \text{if } d_{AA} > d_{\text{avoid}} \\ -\left|d_{\text{avoid}} - d_{AA}\right| & \text{otherwise} \end{cases} \tag{12}$$

This award aims to prevent AUV collisions. Where d_{AA} is the distance between two AUVs. $d_{\text{avoid}} = 2(r_A + d_L)$

Overall rewards function (r_L) The overall reward function is obtained as the weighted sum of the mentioned rewards:

$$r_L = w_1 r_1 + w_2 r_2 + w_3 r_3 + [w_4, w_5]\, r_E^T \tag{13}$$

where w_1,w_2,w_3,w_4 and w_5 are positive constants. $r_E = [-|\tau_u|, -|\tau_r|]$ decrease overall control effort.

4. SIMULATION RESULTS

This section presents the simulation results for the proposed integrated motion planning and control of multi-AUVs. The AUV training area takes place in a space spanning 250 by 250 m^2. Following a similar paradigm to the cooperative motion planning discussed in Section 2, AUVs are trained as agents to follow designated waypoints based on the algorithm explained in Section 3. During the training phase, three AUVs are used, but simulations involve four AUVs to demonstrate generalizability. Nevertheless, this number can change depending on the need. Two test scenarios are exhibited in this paper. The first scenario involves consecutive waypoint tracking under nominal conditions. The waypoints are in varied coordinates to demonstrate the algorithm's generalization ability. The second scenario investigates the algorithm's performance in the presence of obstacles and underwater currents.

4.1 DRL parameter configuration

Double-layer fully connected actor-critic networks with 400 and 300 neurons, respectively, are utilized. It should be noted that the actor and critic have the same structure. Ornstein-Uhlenbeck process noise is employed to select actions, ensuring comprehensive coverage of the state and action spaces. The parameters of the noise are determined by (Hadi et al. (2023)). The values of the TD3 parameters are shown in Table 1.

Table 1. Tuning parameters of the algorithm

Parameters	Value
Learning rate of the actor network	0.001
Learning rate of the critic network	0.0001
Memory size	1e6
Smooth update	0.005
Discount factor	0.99
Sample time	0.5
Policy and target delay update	2
Exploration variance	0.1
Noise variance for the target policy	0.1

4.2 Scenario 1

In this scenario, four AUVs are considered to evaluate the system's performance in path planning without obstacles. To evaluate their performance, the objective was to track waypoints starting towards the West and then track destination points in various other directions. The trajectories of each AUV are displayed in Fig. 3. As seen in this figure, all AUVs successfully reach their reference targets. The AUVs are able to adjust their paths without colliding with each other, and line intersections occur at different times.

The linear and angular velocities required to perform this maneuver are shown in Fig. 4, exhibiting normal behavior without oscillations. Their values are also logical for this class of AUVs.

The control signals obtained for each of the AUVs are shown in Fig. 5. It can be observed that these control signals are feasible for implementation.

4.3 Scenario 2

This scenario evaluates the performance of AUVs in a more challenging environment in the presence of obstacles and ocean currents. To account for ocean currents and how they affect AUV movement, motion equations can be

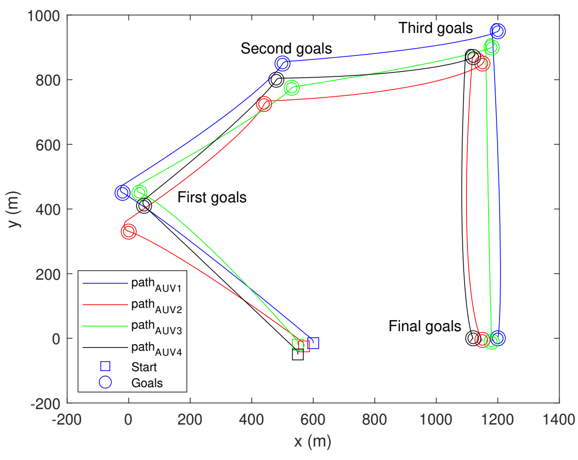

Fig. 3. Trajectories and reference targets of four AUVs in obstacle-free Scenario

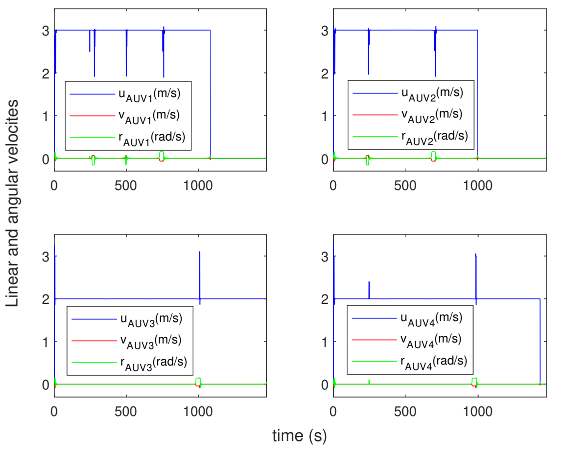

Fig. 4. State variables for four AUVs in obstacle-free Scenario

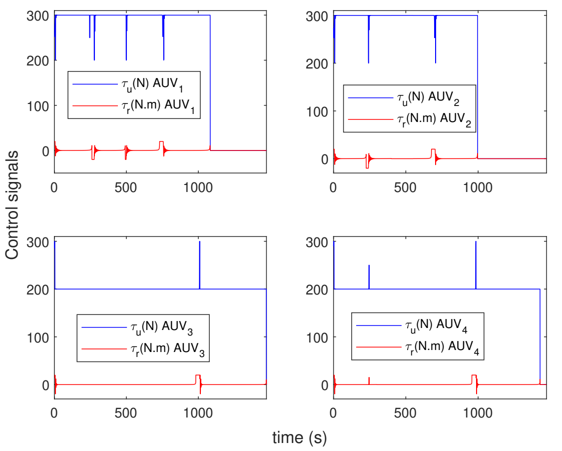

Fig. 5. Control signals of four AUVs in obstacle-free Scenario

expressed in terms of relative velocity (Fossen (2011)). The speed and direction of the ocean current change randomly Hadi et al. (2023), ranging from 0 to 0.2 m/s and 20° to 120° relative to the x-axis, respectively. To accomplish this, three obstacles are strategically placed in positions with a high collision probability. The paths of the AUVs are shown in Fig. 6. It can be seen that the AUVs have reached the reference target without colliding with each other or the obstacles. Linear and angular velocities are shown in Fig. 7. The control signal obtained for each of the AUVs in the presence of obstacles is shown in Fig. 8. The objective of the algorithm is to optimize the attainment of various rewards based on the control objectives outlined in equations 10 to 12. Thus, in the training phase, the aim is to minimize errors in achieving the goal, errors in avoiding obstacles, and the amount of control effort required. When the AUVs approach the targets established using equation 11, they come to a halt upon reaching the target area. At this point, the distance to reach the target area is assessed.

5. CONCLUSION

The research paper introduces a learning-based integrated planning and control algorithm designed for the coop-

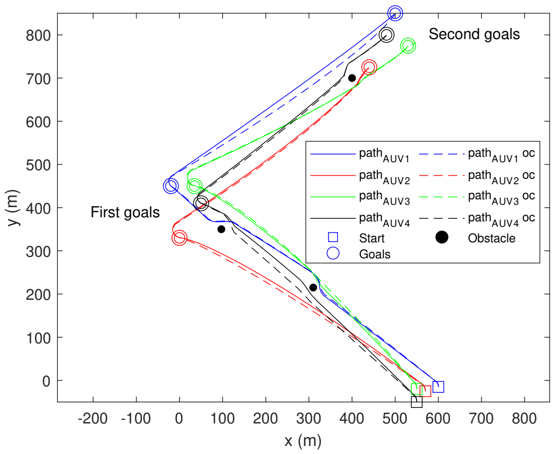

Fig. 6. Trajectories and reference targets of four AUVs in the presence of the obstacles and ocean currents

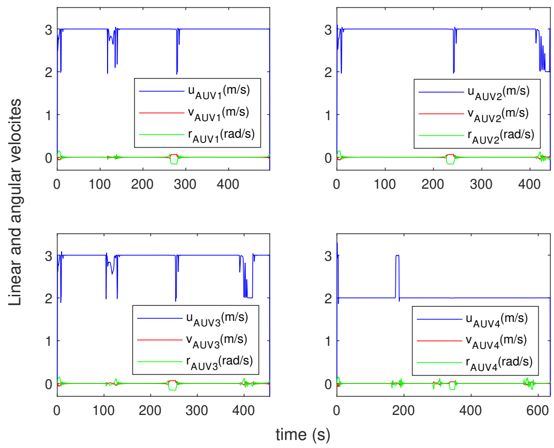

Fig. 7. AUVs state variables in the second simulation scenario

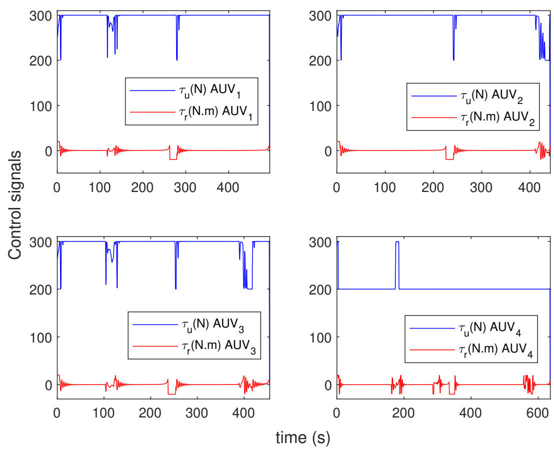

Fig. 8. Control signals of four AUVs for the second scenario

erative motion of multiple AUVs. Leveraging the TD3 algorithm, the proposed approach incorporates a tailored reward and input-output structure, enabling the algorithm to autonomously learn and execute tasks based solely on available data. The simulation results demonstrate the algorithm's proficiency in executing essential maneuvers to track waypoints across diverse directions. In addition, the algorithm showcases the ability to navigate successfully through challenging ocean currents, successfully avoiding collisions with obstacles and other vehicles. In the simulated environment, the control signals generated by the algorithm appear not only effective but also feasible, hinting at their potential real-world applicability. The promising results obtained warrant further exploration, necessitating a more in-depth statistical analysis to understand the algorithm's behavior and robustness. Furthermore, the next development phase can involve implementation tests to validate the algorithm's performance. Developing multi-agent marine systems simulators is another research avenue (Clement et al. (2024)). This multifaceted evaluation will provide valuable information, facilitating the refinement of the proposed algorithm for broader and more complex applications in cooperative AUV motion planning and control.

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