



HAL
open science

LOTUS: Learning from Operational Teaming with Unmanned Systems

Helene Lechene, Benoit Clement, Karl Sammut, Paulo Santos, Andrew Cunningham, Gilles Coppin, Cédric Buche

► **To cite this version:**

Helene Lechene, Benoit Clement, Karl Sammut, Paulo Santos, Andrew Cunningham, et al.. LOTUS: Learning from Operational Teaming with Unmanned Systems. 2024 IEEE Oceans Conference, Apr 2024, Singapour, Singapore. pp.1-5, 10.1109/OCEANS51537.2024.10682309 . hal-04481318

HAL Id: hal-04481318

<https://hal.science/hal-04481318v1>

Submitted on 18 Apr 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

LOTUS: Learning from Operational Teaming with Unmanned Systems

Helene Lechene
Naval Group Pacific
Adelaide, Australia

Benoit Clement
ENSTA Bretagne / CNRS IRL Crossing
Adelaide, Australia

Karl Sammut
Flinders University
Adelaide, Australia

Paulo Santos
Flinders University
Adelaide, Australia

Andrew Cunningham
University of South Australia
Adelaide, Australia

Gilles Coppin
IMT Atlantique / Lab-STICC
Brest, France

Cedric Buche
Naval Group Pacific / ENIB
Adelaide, Australia

Abstract—The LOTUS project aims at improving maritime surveillance. In this context, this position paper presents ongoing contributions, including novel machine learning algorithms for multi-agent systems to be applied to groups of underwater drones involved in surveillance missions. It emphasises incorporating human-machine teaming to bolster decision-making in maritime scenarios. The expected outcomes of this project comprise the robust control of groups of autonomous vehicles, adaptable to environmental changes, as well as an effective reporting method. Mission summaries will be delivered to human operators by way of narratives about the relevant events detected thanks to drones. The integration of this narrative construction powered by machine learning will enhance the overall effectiveness of the team, constituting a significant breakthrough.

I. INTRODUCTION

The maritime area is essential for a variety of activities. Unfortunately, this environment is becoming more complex and potential threats are emerging. To deal with the difficulties of a crowded and contested underwater environment, new advanced undersea surveillance capabilities are needed.

The LOTUS project leverages human-machine teaming to enhance operators' decision-making in a maritime environment. Starting from a collection of static distributed sensors, our proposal is to use underwater unmanned vehicles (UUVs) as a complementary mobile and distributed sensor network to inspect a precise area of interest, typically in a littoral sector. Although autonomous systems are particularly useful when communication is impeded, skilled operators are still to be involved to take decisions. Consequently, both the reliability of a group of UUVs and the dialogue within and with this group are at the core of the project.

Most recent scientific progress in autonomous systems has concerned individual UUVs and has been based on advanced machine learning techniques. Our project targets to extend these approaches to multiple drones and to tackle the challenges associated with human-system interaction. To represent UUVs, LOTUS proposes to use a multi-agent approach to increase robustness, flexibility, and opportunistic functioning.

Multiple UUVs may also lead to a challenging collaborative data processing. In this concern, our solution incorporates considerations about reporting and representing.

The LOTUS project workflow is represented in Figure 1. The first step of our approach is to design a resilient multi-robot UUV system that faces disturbances in an underwater environment (section II), as an extension of previous work on a single UUV. Our objectives include the development of advanced formation control and navigation algorithms for coordinated and covert operations. The second step is to detect, track and report using an original approach based on an event recognition system (section III). The last step is to design efficient interfaces that link the human operator and autonomous agents in order to provide situation awareness (section IV). This development will be integrated in a dedicated simulated environment: LOTUSim (section V). All of these steps are based on human-over-the-loop artificial intelligence. A proposed use case scenario is described in section VI.

II. ROBUST BIO-INSPIRED LEARNING-BASED CONTROL OF GROUPS OF ROBOTS

In the domain of Uncrewed Underwater Vehicles (UUVs), the successful execution of missions extends beyond the simple adherence to user-defined objectives. The ability to navigate unexpected events and challenges is a crucial aspect that demands the evolution of existing methodologies. This part of LOTUS builds upon prior work in Deep Reinforcement Learning (DRL) for UUV control, as established by [1] and [2], and expands its scope to encompass multi-robot systems. The theoretical foundation of this research rests within the paradigm of Multi-Agent Reinforcement Learning (MARL), where collaborative behaviours among multiple learning agents emerge through interactions with their environment and each other. A key feature of MARL is its integration of game theory, guiding agents to maximise rewards while considering social metrics such as cooperation and competition.

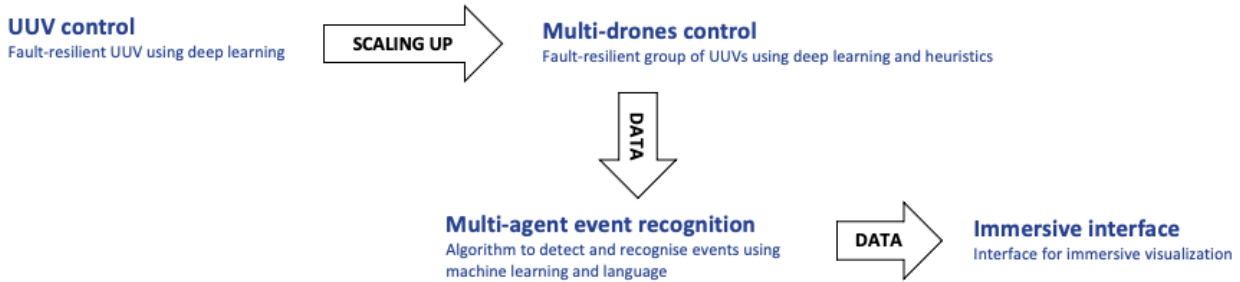


Fig. 1. LOTUS Project workflow

The overarching objective of this research is to refine reinforcement learning processes specifically tailored for pattern formation and obstacle avoidance in a collective of UUVs, in close alignment with the work presented in [3]. Our primary focus is the introduction of innovative heuristics designed to significantly accelerate the learning process. This novel approach, known as Heuristically Accelerated Reinforcement Learning (HARL) [4], [5], leverages biologically-inspired heuristics derived from the collective behaviours observed in groups of animals.

The heuristics used in HARL draw inspiration from the study of animals living in groups, such as schools of fish, flocks of birds, or herds of mammals. These collectives exhibit remarkable behaviours that facilitate effective navigation, resource location, predator avoidance, and communication. Such behaviours emerge from interactions and coordination among individual animals, often occurring without central control or explicit communication.

The incorporation of biologically-inspired heuristics serves the purpose of significantly reducing the exploration space and guiding agents toward more promising actions. These heuristics are applied in various ways, including initialising the agent's policy with a heuristic policy, shaping the reward function to provide guidance, or biasing the agent's exploration toward heuristic-driven actions. The overarching goal is to develop highly efficient and adaptable algorithms capable of handling intricate tasks that require coordination, collaboration, and decentralised decision-making within a group of UUVs.

This research framework within the domain of MARL, coupled with the application of HARL techniques, holds promise for advancing the collective performance of UUVs. The integration of biologically-inspired heuristics offers a compelling avenue for achieving efficient and adaptable algorithms, paving the way for advancements in autonomous multi-agent systems. As we delve deeper into this exploration, our findings may contribute not only to the field of underwater robotics but also to broader applications involving decentralised decision-making and coordination among autonomous agents. In subsequent sections, we will dig into the specific methodologies, experiments, and results that constitute the backbone of this research endeavour.

III. NARRATIVES FOR MULTI-ROBOT EVENT RECOGNITION

The ability to find unexpected events or objects underwater is strongly linked to the corresponding ability to report about these events and, therefore, build an understandable and coherent discourse towards the mission human supervisor. The swarm should send situational awareness and status updates to the operator, and the operator sends high-level control input to the swarm [6]. The reporting function has been quite largely covered when managing a dialogue with one agent only, but remains a true scientific challenge when dealing with as many points of view and interlocutors as a swarm can generate. Indeed, during complex missions executed by groups of autonomous agents, drones go through multiple events that are logged in their memory devices. Due to the large amount of data generated in these missions, it is virtually impossible for an operator to keep track of every event and its consequences in real time, even when high-speed communication between the operator and the drones is available (which is hardly the case). To efficiently monitor such campaigns, it is also essential to understand the operational requirements, from continuous updates during the mission to final reporting post-operation. This task requires a diverse range of skills and knowledge that are hard (if not impossible) to obtain by current deep learning methods, whose main contribution relies on finding complex patterns, given large data sets. Instead, an intelligent autonomous system capable of dealing with campaigns monitoring and report generation should also take into account the expert knowledge. Approaches based on knowledge representation will allow operators to get explainable outputs, in contrast to many commonly used machine learning algorithms [7].

The preliminary results outlined in our previous work [8] encompassed several of these challenges, including the extraction of high-level events from continuous data, the efficient communication and interaction with operators, and leveraging expert knowledge to aid in accurate event identification and operator interaction. Therefore, we propose an extension of the work reported in [8] including the following novel aspects:

- 1) An extension of the event recognition system proposed in [9] towards recognising joint actions in multiagent

systems. This extended system will have the following contributions with respect to state-of-the-art systems:

- The use of a high-level formalism to identify sequences of events, classified by deep learning methods;
 - The development of a distributed version of an event-recognition system, whereby the computation will be shared by the various agents in the mission;
 - The fusion of the knowledge obtained by the multiple agents into a single (consistent) description of the events, actions and tasks observed. We may here consider using pseudo-formalisms commonly described in narratology such as Bremond's "Logic of Narrative Possibilities" [10], making the translation into natural language more accessible to the common human user.
- 2) Experiments on using the system developed in the previous item for generating compact mission descriptions from the data obtained by simulated multi-maritime vessel tasks;
 - 3) The efficient translation of the compact mission descriptions obtained into narratives expressed in natural language.

IV. IMMERSIVE NARRATIVE VISUALISATION FOR UNDERSTANDING AUTONOMOUS MARITIME VESSELS

The expected complexity of multiple and nevertheless coherent missions/data will be addressed through immersive information spaces with which users will interact. The swarms may be composed of a large number of UUVs and communication links can be unreliable, requiring the human operator to understand a significant amount of information when communication links are re-established. This challenge is compounded by the fact that:

- 1) unexpected events may have occurred that must be reported and,
- 2) that the information is highly spatial in nature. These compounding factors create situations that place operators under high cognitive load.

Narrative visualisation combines narrative techniques and information visualisation to communicate a consistent and coherent view of information that is based on the user's mental model of the situation being explained. Applying narrative visualisation to an autonomous system maritime use-case can address the challenge of communicating decisive events from swarm information. Furthermore, the spatial nature of maritime data is ideally suited to immersive visualisation and analytics, leveraging the perceptual affordances of virtual reality (VR) to accurately represent spatial relationships [11]. The combination of narrative visualisation and immersive analytics, *i.e.* immersive narrative visualisation, can provide seamless mission-report summaries to human operator.

The work will be undertaken in two stages. In the first stage, techniques for visually communicating historical simulated swarm data will be developed and evaluated, supporting a

scenario of explanation in post-action review. Through interaction, the user will distinguish different levels of detail for each agent in the zone, causal relationships amongst the events, and explanations about the anomaly. The second stage will explore techniques to support real-time scenarios where the explanation may evolve over time, and decisive events occur while using the system. A novel cognitive model will be developed that considers physiological sensors in the VR headsets (e.g. eye-tracking) and presents relevant narratives to the operator's current task. Through embodied interaction in the immersive environment, the user will be able to explore the situation and intervene with automated assistance about the action to be triggered. The techniques developed throughout this research will be validated through controlled user studies that will compare users' cognitive load and situational awareness between the new methods developed and current approaches [12].

V. PLATFORM: LOTUSIM

The tasks described in section VI will be executed in a dedicated simulated environment: LOTUSim. The simulation platform should gather each component required for providing remote undersea surveillance, permitting strategic experimentation of algorithms produced with a batch of operational scenarios for mission planning and conduct.

LOTUSim will be developed as an operational simulator. The simulation will integrate the physical conditions of an *underwater environment* as input data, leveraging data collected from sensors in a multi-agent setting. New *sensor* deployment strategies that benefit from a multi-agent approach (robust, flexible, decentralised), assessing different kinds of sensors combination given different metrics for improving surveillance (e.g: event detected and classified, usability investigation, operability). The platform will allow to establish communication protocol between a static and a mobile network composed of drones, events will be detected and explained to the operator (*sense-making*). These events should support the decision using an immersive interface for visualisation. Multi-robot *coordination and cooperation* are at the core of our multi-agent system research and development in robotics and algorithmics. The simulator is configurable with different *data and scenarios*, allowing for future *mission autonomy* and scheduling once experimented. This digital environment permits experimentation with a batch of scenarios for mission planning and conduct, ensuring flexibility in this collaborative sensing. It should be done at reduced costs and risks, while being the only way of training models based on machine learning, especially reinforcement learning aiming at drone robustness, that requires a number of iterations that only simulation can provide. As a digital twin approach, the simulation provides a *proof-of-concept* (POC) for autonomous sensor processing of a distributed sensor networks mounted on drones.

From a technical point of view, a good simulator should support different types of vehicles, sensors, and environments with accurate representation of hydrodynamic/hydrostatic forces

[13]. In addition, to simulate multi-robots, simulator should consider to integrate multi-agent system and support large worlds [14]. Lastly, the capacity to display realistic rendering is a great option [13], [14]. Studies [13], [14] presented comprehensive comparison of existing simulators. Figures 2 and 3 offers an extended comparison, using the same criteria.

Simulators for marine robotics can be divided into two categories [13]: surface vehicles and underwater vehicles. Popular surface simulators include USVSim [15] where the focus is to model environmental factors such as waves, wind and water currents. While UWSim [16] and UUV Simulator [17] are the two most widely used options for underwater simulation. Plankton¹ is an extension of UUV Simulator for ROS2 [18]. An alternative is the Stonefish Library [19] which supports standard sensors and has a better approximation of hydrodynamic forces. The simulator supports advanced rendering of underwater scenes. LRAUV is the first simulator that allow multi-robot marine missions [14]. Last but not least, Liquid AI is an open source simulator using ROS2; as a Data Distribution Service (DDS) middleware communication for third party applications, easy to use system with a publisher/subscriber system. Gazebo plugins system is used to integrate complex environmental simulator (x_{dyn}^2 , $asv_wave_sim^3$). Realistic rendering could be done in Unity, including visualization of wave and weather (sky, clouds and rain). Liquid AI is the first tool aiming at simulate both underwater and surface vehicles, plus environmental conditions for multi-robot marine missions using multi-agent approach (Figure 3). For all these reasons, LOTUSim will be based on Liquid AI.

VI. USE CASE

The proposed scenario is related to Mine Counter Measures (MCM). UUVs have been demonstrated to be particularly effective at detecting mines buried under, sitting on, or suspended above the seabed. Side scan or synthetic aperture sonar is one particular modality for detecting Mine Like Objects (MLOs) by flying the vehicle above the seabed, however the swath coverage from a single vehicle can be quite narrow, spanning a few metres to a few 10's of metres, depending on the vehicle's height above the seabed. Since the scan resolution is inversely proportional to the vehicle's height above the seabed, it is preferable to fly the vehicle at a fixed height to achieve a uniform swath. While a single vehicle can cover a large area by flying the vehicle along a raster scan across the area, considerable speed up and coverage assurance can be gained by flying multiple vehicles in parallel formation to acquire multiple overlapping swaths. Machine learning techniques can be then be used on-line or via post-processing to identify MLOs and report back their locations to an operator or other vehicles. Recent developments in autonomous MCM are exploring the use of hybrid teams of vehicles including scanning sonar equipped torpedo shaped vehicles to scout ahead scanning for possible MLOs followed by hovering type

vehicles equipped with different sensing modalities, such as cameras or forward looking sonars, that are then tasked to inspect the potential MLOs close up and confirm the identity of the target.

This hybrid vehicle team forms the basis of the proposed scenario (Figure 4). The deployment of a fleet of autonomous and collaborative underwater agents capable of autonomously assigning tasks to vehicles and sharing the workload requires the implementation of a distributed architecture and multi-agent decision algorithms. This distributed intelligence requires the specification of precise mission objectives that allow the formulation of a multi-robot task allocation problem (MRTA) with the following specificities:

- 1) Communication constraints/challenges between agents (underwater context) - acoustic communication bandwidth is severely limited, this is especially challenging for teams of vehicles with a distributed MRTA;
- 2) Mission hazards (deviation from the initial plan, e.g. detection of cross-currents or opposing currents) that must be managed in real time;
- 3) Robustness to failure of individual vehicles/sensors - this involves dynamic reallocation of tasks based on availability and proximity;
- 4) Energy constraints - a critical priority of the fleet is to ensure the safety of the vehicles, in this case ensuring that they have enough energy to complete the mission and return back. Task allocation must prioritise energy conservation and allow for vehicles to be swapped in and out of the fleet based on energy reserves.

The resolution of the MRTA results in a global mission plan that must be executed by each agent, monitored (detection of deviations), and, if necessary, repaired.

VII. CONCLUSION

The LOTUS should provide a complete coherent task chain allowing persistent monitoring of an area, the automated narrativisation (mission reporting), embedding the multiple actors and their roles, and a new kind of interactive and immersive framework dedicated to visual support of the interpretations of the story narratives. This chain will be tested using a dedicated simulation environment that will incorporate a multi-agent framework with AI algorithms for underwater surveillance to Gazebo and ROS2 with extensions to Unity and Unreal engines. Through simulation, our fleet of drones is required to demonstrate precise behavior at specific moments, even when faced with unforeseen circumstances. They will possess the ability to persist with the mission, undeterred by adverse environmental or operational conditions. Additionally, these simulations aim to generate valuable data that contributes to the analysis, reporting, and representation of a complex multi-agent system. The outcomes of this work will have to be tested in real-life conditions. The accuracy of LOTUSim should then simplify the transfer.

¹<https://github.com/Liquid-ai/Plankton>

²<https://github.com/sirehna/xdyn>

³https://github.com/srmainwaring/asv_wave_sim

Simulator	Hydrodynamics	Hydrostatics	Thruster	Fins	Pressure Sensor	GPS	DVL	Realistic Rendering	Contact Dynamics	Wind	Waves	Water Currents
UWSim	✓	✗	✓	✗	✓	✓	✓	✓, osgOcean	✓	✗	✓	✗
UUV	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗
Stonefish	✓	✓	✓	✗	✓	✓	✓	✓, custom	✓	✓	✓	✓
URSim	✓	✓	✓	✗	✓	✗	✗	✓, Unity	✗	✗	✓	✗
USVSim	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓
LiquidAI	✓	✓	✓	✓	✗	✓	✗	✓, Unity	✗	✗	✓	✗

Fig. 2. Feature comparison of popular simulators used for marine robotics, as an extension of the table proposed in [13]

Simulator	Underwater Hydrodynamic	Surface Hydrodynamic	Multi agent	Realistic Rendering	Large Worlds	ROS2
UUV	✓	✗	✓	✗ gazebo	✗	✗ ROS1
DAVE	✓	✗	✓	✗ gazebo	✓	✗ ROS1
StoneFish	✓	✗	✗	✓ bullet	✗	✗ ROS1
LRAUV	✓	✗	✓	✗ gazebo (new)	✓	✓
LiquidAI	✓	✓	✓	✓ Unity	✓	✓

Fig. 3. Feature comparison of popular simulators used for marine robotics, as an extension of the table proposed in [14]

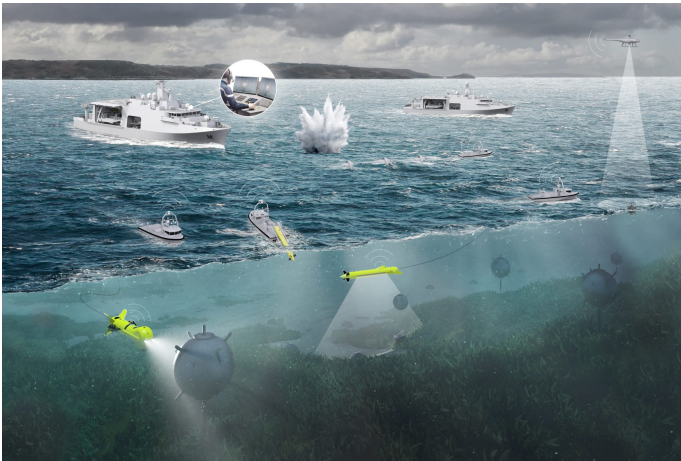


Fig. 4. Mine counter measure overview

REFERENCES

- [1] T. Chaffre, P. Santos, G. Le Chenadec, E. Chauveau, K. Sammut, and B. Clement, "Learning Adaptive Control of a UUV using A Bio-Inspired Experience Replay Mechanism," *IEEE Access*, 2023.
- [2] K. Lagattu, G. Le Chenadec, E. Artusi, P. E. Santos, K. Sammut, and B. Clement, "Drl-based thruster fault recovery for unmanned underwater vehicles," in *2024 Australian New Zealand Control Conference (ANZCC)*, 2024.
- [3] B. Clement, M. Dubromel, P. Santos, K. Sammut, M. Oppert, and F. Dayoub, "Hybrid navigation acceptability and safety," in *AAAI 2023 Fall Symposium Series*, Arlington, 2023.
- [4] R. Bianchi, P. Santos, I. da Silva, L. Celiberto, and R. L. de Mantaras., "Heuristically Accelerated Reinforcement Learning by Means of Case-Based Reasoning and Transfer Learning," *Journal of Intelligent and Robotic Systems*, 2018.
- [5] R. A. Bianchi, L. A. Celiberto Jr, P. E. Santos, J. P. Matsuura, and R. L. De Mantaras, "Transferring knowledge as heuristics in reinforcement learning: A case-based approach," *Artificial Intelligence*, vol. 226, pp. 102–121, 2015.
- [6] A. Hocraffer and C. Nam, "A meta-analysis of human-system interfaces in unmanned aerial vehicle (UAV) swarm management," *Applied Ergonomics*, 2017.
- [7] E. Ntoulas, E. Alevizosand, A. Artikis, C. Akasiadis, and A. Koumparos, "Online fleet monitoring with scalable event recognition and forecasting," *GeoInformatica*, 2022.
- [8] J. A. Gurzoni, P. E. Santos, M. F. Martins, and F. G. Cozman, "Probabilistic logic for multi-robot event recognition," in *2013 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, 2013, pp. 1–2.
- [9] A. Skarlatidis, G. Paliouras, A. Artikis, and G. A. Vouros, "Probabilistic event calculus for event recognition," *ACM Trans. Comput. Logic*, vol. 16, no. 2, feb 2015. [Online]. Available: <https://doi.org/10.1145/2699916>
- [10] C. Bremond and E. D. Cancalon, "The logic of narrative possibilities," *New Literary History*, vol. 11, no. 3, pp. 387–411, 1980. [Online]. Available: <http://www.jstor.org/stable/468934>
- [11] A. Cunningham, "Immersive visualisation of geo-temporal narratives in law enforcement," *International Symposium on Big Data Visual and Immersive Analytics (BDVA), IEEE.*, 2018.
- [12] S. Richir, P. Fuchs, D. Lourdeaux, D. Millet, C. Buche, and R. Querrec, "How to design compelling virtual reality or augmented reality experience?" *International Journal of Virtual Reality*, vol. 15, no. 1, p. 35–47, Jan. 2015. [Online]. Available: <https://ijvr.eu/article/view/2867>
- [13] J. Collins, S. Chand, A. Vanderkop, and G. Howard, "A review of physics simulators for robotic applications," *IEEE Access*, vol. PP, pp. 1–1, 03 2021.
- [14] T. R. Player, A. Chakravarty, M. M. Zhang, B. Y. Raanan, B. Kieft, Y. Zhang, and B. Hobson, "From concept to field tests: Accelerated development of multi-auv missions using a high-fidelity faster-than-real-time simulator," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, May 2023.
- [15] M. Paravisi, D. H. Santos, V. Jorge, G. Heck, L. M. Gonçalves, and A. Amory, "Unmanned surface vehicle simulator with realistic environmental disturbances," *Sensors*, vol. 19, no. 5, 2019. [Online]. Available: <https://www.mdpi.com/1424-8220/19/5/1068>
- [16] M. Prats, J. Pérez, J. J. Fernández, and P. J. Sanz, "An open source tool for simulation and supervision of underwater intervention missions," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012, pp. 2577–2582.
- [17] M. M. M. Manhães, S. A. Scherer, M. Voss, L. R. Douat, and T. Rauschenbach, "Uuv simulator: A gazebo-based package for underwater intervention and multi-robot simulation," in *OCEANS 2016 MTS/IEEE Monterey*, 2016, pp. 1–8.
- [18] S. Macenski, T. Foote, B. Gerkey, C. Lalancette, and W. Woodall, "ROS2: Design, architecture, and uses in the wild," *Science Robotics*, 2022.
- [19] P. Cieślak, "Stonefish: An advanced open-source simulation tool designed for marine robotics, with a ros interface," in *OCEANS 2019 - Marseille*, 2019, pp. 1–6.