



D3.4 Autonomous location and recovery system for tagged gears

Report on the autonomous and recovery system for tagged gears. Integration of the enhanced localisation system with existing robotic tools (IRIS ROV/AUV) and a new net recovery payload developed for robotic systems, and increasing of the TRL, with the development of new human machine interfaces (with input from fishers) for robot control and supervision, and custom designed robot deployment and recovery procedures suited to fishing operations. IRIS (previous robot) will be upgraded with automated close-range net detection and recovery control manoeuvres; and also robot operation from smartphone with simple human interaction to allow its use by untrained personnel.



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Summary NETTAG+ Project

NETTAG+ aims to provide a portfolio of three innovative smart and sustainable solutions to address the negative impacts of abandoned, lost or otherwise discarded fishing gear (ALDFG) on marine life and habitats. NETTAG+ will be based on synergistic activities between the fisheries industry, scientists and NGOs to develop three solutions to PREVENT, AVOID and MITIGATE the harmful impacts of ALDFG.

NETTAG+ will PREVENT marine litter derived from fisheries activities, AVOID loss of fishing gears, and MITIGATE harmful impact by removing existing ALDFG. These three solutions will jointly contribute to reduce ALDFG and marine pollution, namely by: reducing the introduction of hazardous chemicals and microplastics originating from ALDFG; reducing ghost fishing, bycatch and entanglements of sensitive or endangered species on ALDFG; and improving mapping, tracking and recovery technologies to retrieve ALDFG.

NETTAG+ aims to upgrade and upscale the integrative preventive approach that started in the previous NetTag project, and aims to replicate it in Mediterranean regions, providing the fisheries industry with three smart and environmentally-friendly solutions to reduce ALDFG and prevent the environmental impacts of fishing gears. The three solutions will be developed to maturity (TRL 7-8) by the end of the project, and will be tested, validated and demonstrated in real conditions in Atlantic and Mediterranean countries, namely Portugal (PT), United Kingdom (UK), Spain (SP), Italy (IT), Croatia (HR) and Malta (MT). NETTAG+'s ambition is to change the paradigm of the fisheries industry, aspiring to transform the societal perspectives about the role of fishers as Guardians and Cleaners of the Ocean. NETTAG+ will empower the sector to take effective actions to address marine pollution, promoting their role as key actors to tackle marine pollution.

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Executive Summary

This deliverable presents the NETTAG+ project's technical developments to provide tools for autonomous location and removal of tagged Abandoned, Lost, or otherwise Discarded Fishing Gear (ALDFG).

The project offers an integrated strategy based on three core components, which are the prevention of gear-related marine litter, the minimization of gear loss during fishing operations, and the autonomous detection of ALDFG. The present report is related to the minimization of gear loss, using acoustic tags developed for the purpose of possible localization of lost gear. In particular describes the developments of a robotic-based solution (implemented in the IRIS robot prototype) capable of autonomously detecting, localizing, and approaching the tagged gear to support the retrieval process.

Through the deployment of advanced autonomous underwater vehicles (AUVs) and robust state estimation algorithms, the project demonstrates the feasibility of non-invasive, cost-effective methods for marine debris mitigation. Field trials and simulation results provide evidence supporting the proposed framework's effectiveness in real-world conditions.

1 Introduction

Abandoned fishing gear in the ocean pose a significant threat to marine ecosystems, primarily due to “ghost fishing”, which is a phenomenon where lost or discarded gear continues to trap and kill marine animals indiscriminately. This issue contributes to marine biodiversity loss and has led to increased interest in developing technologies for the detection, tracking, and recovery of this harmful debris.

To address this challenge, various methods have been proposed, including acoustic and vision-based detection systems, state estimation algorithms for localization, and mechanical tools for retrieval. Among the most promising platforms capable of integrating these capabilities are Autonomous Underwater Vehicles (AUVs), which offer the potential for efficient and fully autonomous underwater recovery operations.

This work is developed under Work Package 3 of the NETTAG+ project, which aims to create an end-to-end recovery system for ALDFG, targeting tagged gear located throughout the water column and on the seafloor. The system includes the detection and approach steps to tagged fishing gear using a fully autonomous solution.

In a previous project (NetTag), an initial version of a small robot was developed to assist in the process of identification, assessment, and recovery of lost fishing gear. This robot (IRIS) was used by fishers operating in ROV mode (Remotely Operated Vehicle, teleoperated from the surface by a human operator), to demonstrate the capability of inspection of the local conditions of the lost gear.

In the NETTAG+ project the initial robot prototype was taken as a basis for development of automated solutions for location of tagged gear and to demonstrate capabilities in the recovery of it. Thus, a new robotic system evolved from the existing prototype with the additional technical functionalities (such as improved navigation, additional sensors, and additional payload capacity), and to incorporate autonomous approach manoeuvres that can locate and approach tagged gear without direct human control. A new system for attaching a recovery line to the lost gear was also developed and incorporated in the IRIS vehicle.

The vehicle is also used in WP4 of NETTAG+ to carry acoustic imaging sensors to detect untagged lost fishing gear.

In WP3, and in what concerns the present report, this work is related to Task 3.4, addressing the development of automated tools to support the location and retrieval of tagged gear. Thus it is



closely related to work developed in the work package, namely with the acoustic tags developed in Task 3.1 and the locator devices and methods in Task 3.3. These systems provide measurements of distance to the tag that are used in the robotic vehicle to autonomously navigate it to the tag.

The robotic location and approach to the tags is performed using at least one acoustic tag (developed in Task 3.1) on the fishing gear and with one or two (preferably) locator devices that interrogate the tag.

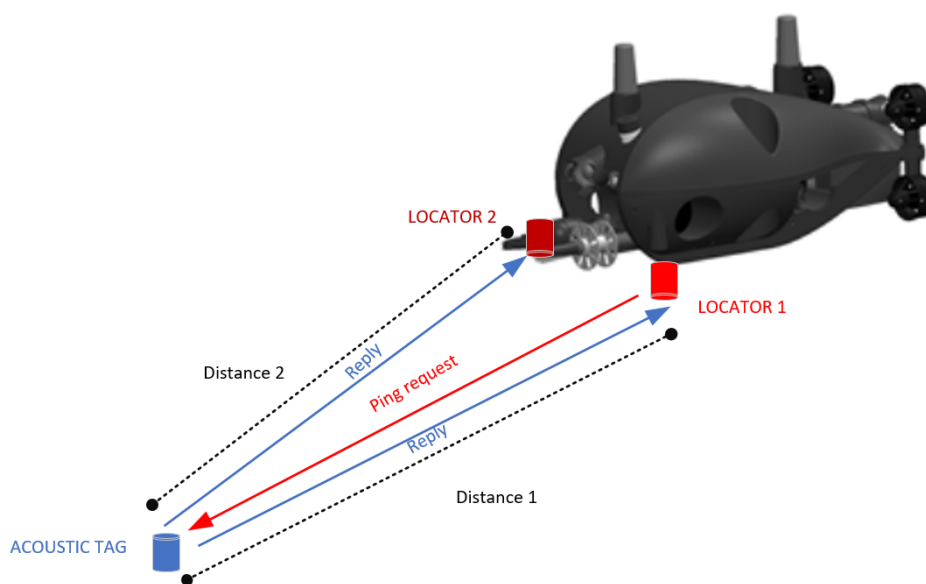


Figure 1. Acoustic tag locating process from IRIS robot

The locator on the vehicle periodically interrogates the tag, and the tag replies. The locator(s) receive the reply to enable range and/or direction measurement (possible when more than one locators are used in the vehicle), see Figure 1.

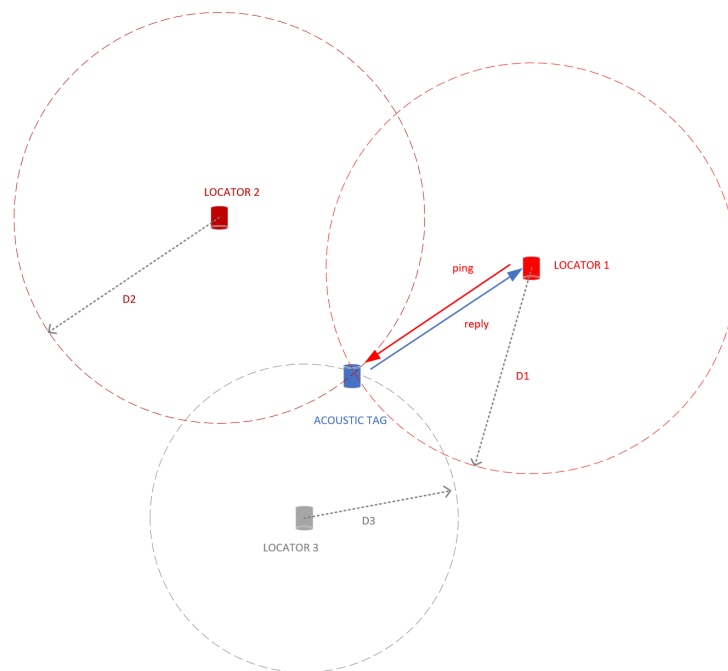


Figure 2. Multilateration

This process of multilateration (see Figure 2) uses the time-of-flight principle where, the time between the ping request and received response can be used to estimate the distance between the pinging device (locator) and the target replier (tag). Taking this distance from different positions (as it is done when using the locator on board of a fishing vessel) or from different locators at known positions can determine the position of the target. As it is shown in the figure the intersection of distances D1 and D2 gives 2 possible positions where this ambiguity can be resolved with an additional measurement D3.

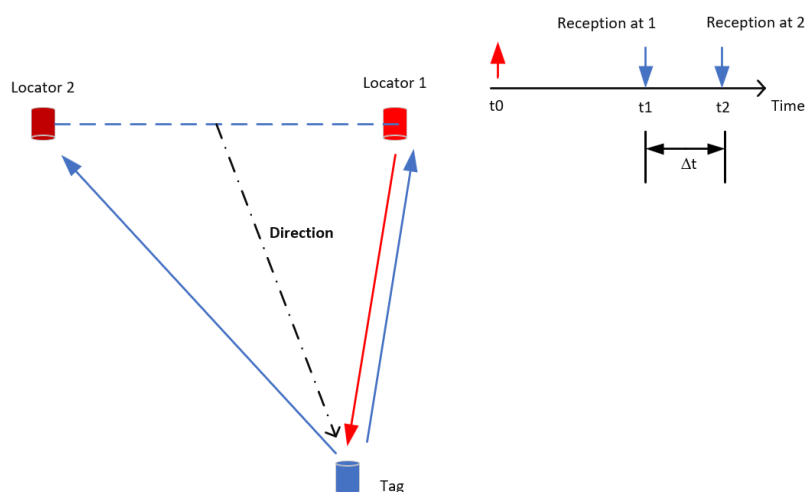


Figure 3. Direction and range estimation with two locator devices

In the case of the robot IRIS, it is equipped with two locator devices. One of them makes the ping request at time t_0 that is answered by the tag. The reply is listened at different times in each of the locators (t_1 and t_2) and thus the time difference (Δt) can be used also to estimate a direction along with a range.

As IRIS has its own position, the distance to the tag can be measured the approach phase even if it only uses one locator (with two, direction estimation provides additional information), where the AUV estimates the location of the ALDFG using multilateration along with Kalman Filtering techniques, allowing the vehicle to track the gear's position and autonomously navigate toward it. As the AUV reaches the gear, the retrieval phase is taken into action, which involves a custom-designed mechanical system capable of attaching to the fishing gear, allowing the AUV to secure and drag it toward the surface without direct human intervention, or to attach a standalone retrieving line to the gear.

Initial testing of the detection and tracking subsystems has been successfully conducted in simulation environments, validating the feasibility of the approach and laying the groundwork for real-world implementation.

2 ALDFG Retrieval

The primary causes behind the presence of ALDFG include equipment wear and tear, mechanical failures, collisions between fishing gear, adverse weather conditions, human error, and, in some cases, intentional dumping (Ritchie, Samborska, & Roser, 2023).

Considering the robust nature of the materials used, which are engineered to withstand physical, chemical and biological breakdown, ALDFG can remain in the marine environment for decades, causing prolonged harm to ecosystems. The global community has recognized these impacts, prompting the launch of both preventive and retrieve-focused initiatives. As a result, there has been a growing investment in research and innovation aimed at developing effective technologies for detecting and removing these persistent threats from the ocean.

2.1 Acoustic Sensors and Technology for the Localization of ALDFG

When localizing ALDFG underwater, acoustic sensors are the primary tool, as electromagnetic signals are heavily attenuated by seawater's high absorption rate, making them impractical. Consequently, acoustic communication becomes essential. Given that the speed of sound underwater is approximately 1500 m/s^{-1} , it offers a reliable means of maintaining connectivity where other communication methods fail. A wide range of acoustic sensors and technologies is available and commonly employed for detecting ALDFG in underwater environments:

- Imaging Sonar produces high-resolution 2D or 3D acoustic images of the seafloor and objects.
- Side-Scan Sonar provides wide swath images of the seafloor using acoustic reflections.
- Multibeam Echo Sounder (MBES) generates detailed bathymetric maps.
- Synthetic Aperture Sonar (SAS) ensures high-resolution imaging with extended range and finer details than side-scan sonar.
- Acoustic pingers to track gear equipped with acoustic tags.
- Ultra Short Baseline (USBL) systems to track the position of acoustic sources, like tagged gear, relative to the receiver (this technology was used in IRIS to locate the acoustic tags).
- Long Baseline (LBL) systems use multiple seabed-mounted transponders to triangulate AUV or target positions.

For the removal of ALDFG in underwater environments sound-based technologies, including imaging sonar, SSS, MBES, SAS, acoustic pingers, USBL, and LBL, are the only viable options. However, these technologies serve different roles within the detection process.

Systems like imaging sonar, SSS, MBES, and SAS are primarily suited for detection and classification, particularly when the lost gear is within the limited sensing range of these instruments. Their main application is capturing seafloor imagery that can later be analyzed for object classification.

On the other hand, acoustic pingers, USBL, and LBL are designed for long-range detection and localization, relying on two-way acoustic communication between the vehicle and the tagged gear. These systems are more effective in tracking and pinpointing gear positions over larger areas.

2.2 Mechanical Systems for the Removal of ALDFG

After the localization methods to reach the gears, they still need a type of mechanical system capable of attaching the AUV to them and retrieving them to the surface. There are several peer-reviewed studies featuring systems, such as claws, hooks, or capture mechanisms, used for underwater recovery.

Presenting the techniques used in ALDFG detection also highlights the numerous technical challenges associated with their retrieval, such as gear entanglement, depth limitations, and the substantial effort required to lift these systems to the surface. Over the years, a variety of recovery systems have been developed to address these challenges. These systems are typically deployed using AUVs, ROVs, or directly from surface vessels. The primary recovery mechanisms can be broadly categorized into grasping tools, like claws or grippers, hooking or latching systems, and tow-based grapple devices, each of which is suited for different operational scenarios, depending on gear type, water depth, and available vehicle capabilities.

Claw-based systems are among the most used for direct retrieval of small to medium-sized debris. These robotic manipulators, often mounted on ROVs or AUVs, allow precise grabbing using visual or sonar feedback, as they can be remotely operated to latch onto nets or ropes, enabling retrieval without requiring direct human intervention. However, their effectiveness is constrained by the lifting capabilities of the underwater platform, particularly when handling large or heavy gear, or when attempting to address these limitations, such as the use of



hydraulic claws, which still depend on the vehicle's thruster power, and adaptive grippers specifically designed to conform to non-uniform geometries.

Hook and line systems offer an alternative method by attaching a buoyed line to the lost gear, which is later retrieved manually or by the surface vessel. These systems are simpler and more scalable for mid to deep water deployments. The AUV or ROV is used to locate the gear and deploy a tagging hook that remains attached while a surface buoy floats up. This allows operators to later pull up the gear using winches or cranes. This method reduces the demand for underwater vehicles, also inducing dependency on surface vessels.

Recent studies have explored hybrid and autonomous systems that combine sonar-based detection with intelligent grasping algorithms to improve recovery accuracy. Some research projects have combined SAS detection with AI tools for controlling robotic arms in precision grasping. These systems not only include SAS, but also other techniques like imaging sonar, MBES, and SSS, which offer higher autonomy and can adapt to several types of environments. For instance, the use of a group of acoustic sensors based on two-way communication wouldn't allow the combination of AI tools for robotic arms control, as these are mainly designed for localization and control of the vehicle trajectory to approach the gears.

3 Robotic System to Support Autonomous Location and Recovery of Tagged Gear – IRIS Underwater Robot

The IRIS (Inspection and Recovery Intelligent System) AUV has earned significant recognition for its compact design, which enhances portability and facilitates underwater maneuverability. Its modular architecture also provides clear operational advantages. AUVs are a comparatively recent innovation in ocean exploration, with their adoption growing rapidly thanks to their ability to gather large volumes of data at relatively low operational costs.

Initially, AUVs were often large and heavy, particularly for deep-sea missions, under the assumption that bulkier designs were inherently more robust. However, this is not always the case. If the pressure hull is properly engineered to withstand high pressures, smaller AUVs offer significant benefits, such as reduced logistical requirements and simplified deployment. Furthermore, being either remotely operated or autonomous, AUVs offer safer alternatives to traditional manned submersibles.

This chapter presents the key characteristics of the IRIS AUV, highlighting why it is a strong fit for autonomous localization and recovery of tagged equipment in underwater environments (Cruz, Matos, Almeida, & Ferreira).

3.1 IRIS Underwater Robot

The IRIS robot is an autonomous underwater vehicle that can operate either in autonomous mode (AUV) or in remotely operated one (ROV).

An initial prototype was developed in an earlier project (Figure 4).



Figure 4. IRIS robot prototype developed in the previous project

In this project in Task 3.4 a relevant set of technical upgrades and developments were made. These can be summarized in:

- Mechanical redesign with integration of additional payload carrying capacity with additional flotation foam, simultaneously reducing drag and improving locomotion capabilities.
- Integration of the developed locator devices in Task 3.3 in substitution of previous acoustic locator devices, and in particular with the software integration of the USBL capability with the measurement of differential acoustic receive time.
- Redesign of the cameras to reduce size and improve available vehicle space.
- Integration of a new higher-quality IMU system to improve navigation.
- Redesign of the internal main electronics system to incorporate the new sensors, integrate new functionalities (such as additional internal vehicle status sensing) and improve system reliability.
- Development and integration of a new system for attaching a retrieval line to the lost gear.
- Increase in the vehicle's overall depth rating (now up to 500m) with the design and implementation of new pressure vessels for the electronics (main and power cylinders and cameras).
- Development of an autonomous navigation and control manoeuvre for autonomous location and approach to the target gear.

Figure 5 and Figure 6 illustrate the IRIS AUV along with its onboard sensors. The vehicle is equipped with eight thrusters, enabling full six Degrees of Freedom (DoF) manoeuvrability. This configuration allows precise control of translational motions (surge, sway, and heave) as well as rotational motions (roll, pitch, and yaw).

However, for the mobility part, the AUV must have real-time information on its own position and on the surrounding environment. For its own navigation and localization, the AUV uses dual Real-Time Kinematic (RTK) GNSS antennas to provide high-precision positioning. The two antennas are mounted on top of the vehicle so that, when the AUV approaches the surface, they emerge from the water to receive stronger satellite signals. This is particularly useful after a dive, enabling the vehicle to correct any accumulated positional drift. While underwater, where GNSS is unavailable, the AUV relies on dead reckoning, based on the fusion of data from the Doppler Velocity Log (DVL) and the Inertial Measurement Unit (IMU). The DVL sensor is positioned on the bottom of the vehicle to estimate the vehicle's velocity relative to the seafloor

using acoustic Doppler shift, while the IMU provides heading and orientation. By integrating these velocity and heading measurements over time, the system estimates the AUV's position. However, even small sensor inaccuracies can accumulate over time, leading to gradual drift from the AUV's true location.

IRIS is equipped with two imaging cameras, one on the front and the other on the rear, enabling it to manipulate a claw system or hook. These, along with the imaging sonar positioned next to the front camera, provide data about nearby obstacles. With the data provided by these sensors, the AUV can be manually operated to avoid such objects or perform any type of operation.

Figure 6 not only shows the DVL sensor but also a multibeam sonar on the rear, which can provide bathymetric data of the seafloor or objects within the water column by emitting multiple acoustic beams for mapping.

The AUV is also fitted with two acoustic transponders, mounted on the left and right sides of the vehicle's front section. These cylindrical, downward-facing devices are designed to emit acoustic pulses from the surface, targeting the location of tagged gear positioned either in the water column or on the seafloor.

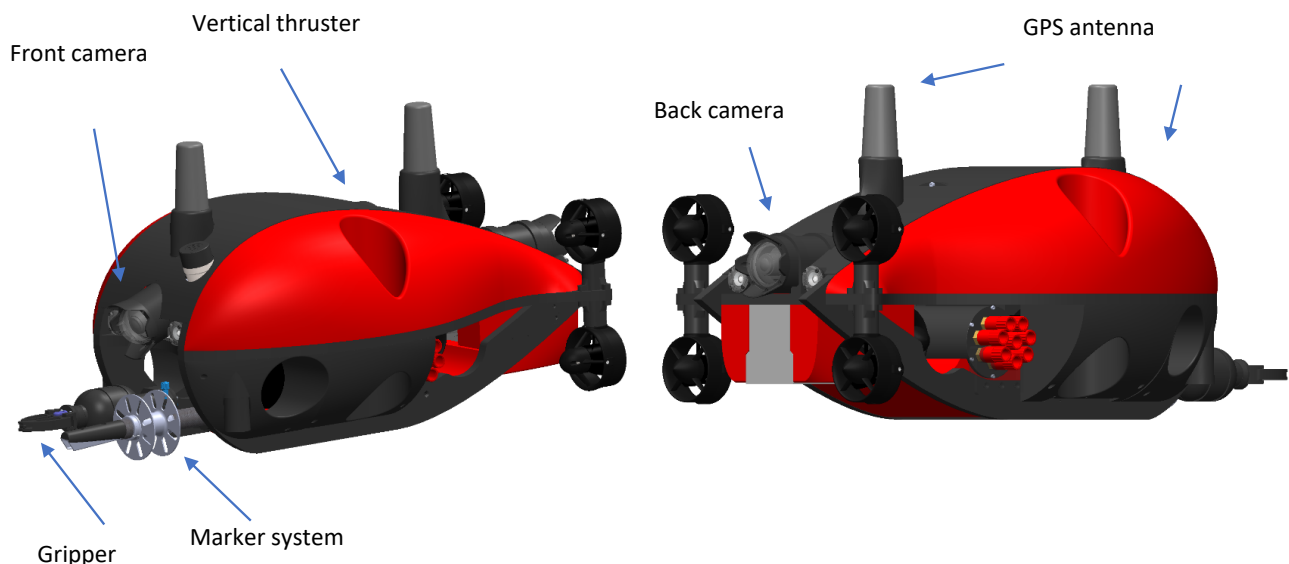


Figure 5. IRIS front and back view

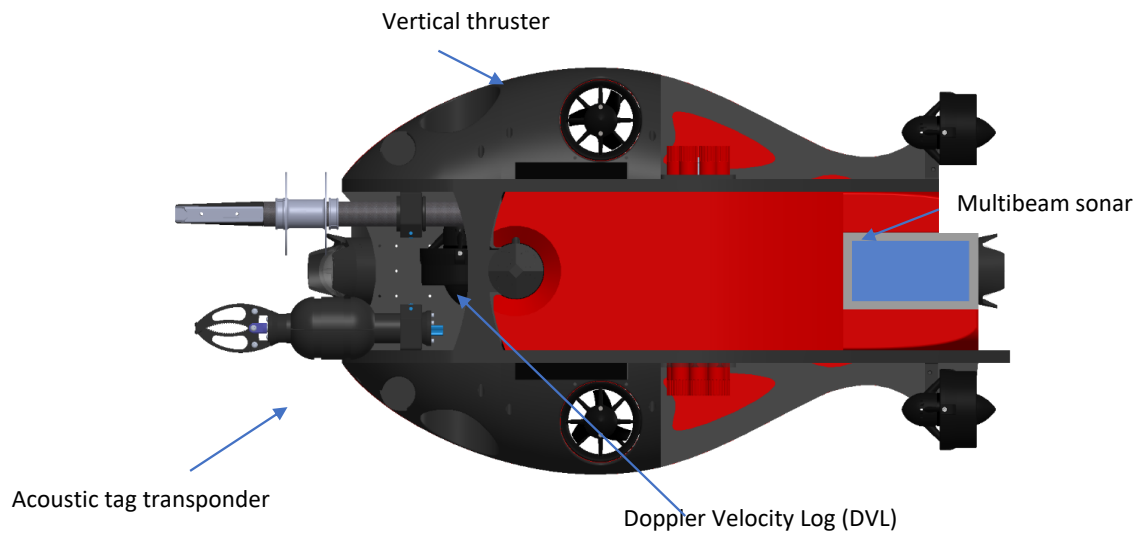


Figure 6. IRIS bottom view



Figure 7. IRIS robot

The upgraded vehicle incorporating the developments performed in Task 3.4 can be seen in Figure 7 with central cover removed showing the main electronics cylinder and with the new hydrodynamic shape provided by the foam clearly visible in red.

3.2 Gear Marking and Attaching System

As illustrated in Figure 8, two different mechanical devices were designed to attach to fishing gear.

The claw system, as previously described, is remotely operated and intended for directly grasping and retrieving fishing gear. Operators control the claw with assistance from onboard visual cameras. While effective for handling small to moderately sized items, it encounters limitations when dealing with larger or heavier gear, as the required lifting force may surpass the AUV's capacity.

A secondary mechanical system was developed, consisting of a coiled wire attached to a carabiner (Figure 8, Figure 9). Using the claw, the carabiner is secured to the gear, and as the AUV moves away, the wire unspools, releasing a buoy that ascends to the surface to mark the gear's position. This allows a surface vessel to recover the gear using manual, hydraulic, or trawl winches.

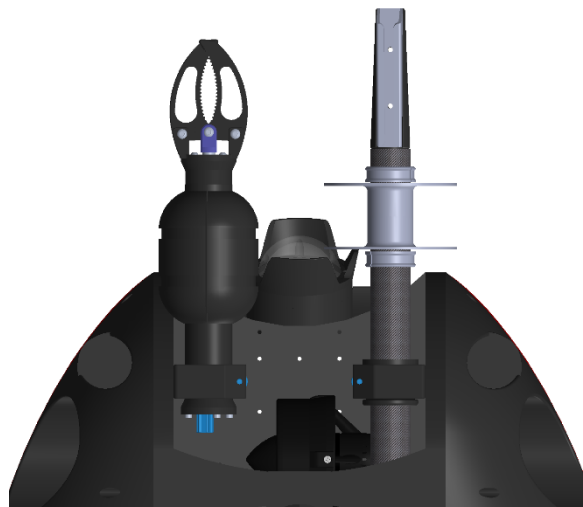


Figure 8. Gripper and gear attaching and marker system



Figure 9. Carabiner and pulling line with flotation

3.3 Robotic Location Support Use Cases

This section presents representative use cases demonstrating how the IRIS AUV and its onboard components support autonomous location and recovery tasks. The robot development was performed in cooperation with the participant fisher in order to obtain a versatile tool. The imaging capabilities were the results of specific requests from the fishers that were interested not only in being able to see and understand why the gear was lost in a particular place but also to allow other possible small inspection capabilities such as inspection of the fishing vessels.

3.3.1 Tethered Mode for Site Inspection

In this configuration, the IRIS AUV is operated with a tether (cable) to conduct close-range inspections of suspected gear sites. The tether ensures continuous power supply and real-time communication, providing operators with live video feeds from onboard cameras, direct thruster control and enhanced manoeuvrability in constrained or cluttered environments. This configuration ensures reliable operation and precise navigation, making it well-suited for inspection tasks in complex seafloor conditions.

However, the main limitation lies in the restricted operational range due to the tether length, making it unsuitable for extended autonomous missions.

3.3.2 Tethered Deployment for Gear Marking and Retrieval

In this use case, the IRIS AUV operates in a tethered configuration to locate fishing gear through a combination of visual and sonar-based localization. Once the gear is identified, a mechanical system is used to attach a buoy to the gear, allowing for its retrieval by a surface vessel.

While effective, this approach requires human intervention to complete the recovery process. It is best suited for medium-depth operations, where the gear can be accessed without the need for specialized deep-sea equipment.

3.3.3 Autonomous Retrieval with Gripper System

When the gear is lightweight, IRIS can be used in a fully autonomous retrieval mode. It utilizes acoustic locator devices for localization and approach, and a robotic claw mechanism to grasp and recover the target. This mode is an end-to-end retrieval process without surface intervention.

The primary limitation is related to the AUV's lifting capabilities, as its propulsion system and buoyancy restrict recovery to light objects only.

Beyond the current operational modes, the IRIS AUV also holds potential for future use in detecting untagged fishing gear. Although not within scope of this deliverable, the AUV can autonomously survey large areas using its onboard imaging sonar to identify objects or anomalies on the seafloor. This function is particularly relevant for upcoming tasks under WP4, as it supports the detection of ghost nets and debris without relying on pre-installed acoustic transponders.

These use cases highlight the modularity and flexibility of the IRIS AUV in supporting gear recovery operations. Whether operated in tethered mode for precise control, used to mark gear for surface retrieval, or deployed autonomously for light gear recovery, the vehicle supports various operational workflows adapted to different field conditions.



4 Simulation Environment for Testing and Validating Robotic Control and Navigation

Simulators play a crucial role in the development and validation of robotic systems, particularly due to the complex integration of diverse design aspects that must be tested prior to real-world deployment.

One of the earliest and most widely recognized tools is UWSim, which, despite no longer being actively developed, remains maintained. UWSim is primarily utilized as a visualization platform for simulating underwater sensors. However, it falls short in simulating accurate vehicle dynamics and hydrodynamics and does not support manipulator dynamics, offering only kinematics solutions.

Gazebo is another widely adopted simulation environment, but it also lacks native support for underwater hydrodynamics. Furthermore, its limited rendering capabilities prevent realistic underwater visual simulation. Although Gazebo can be extended through custom plugins, such as the UUV simulator, these extensions still fail to accurately simulate manipulator hydrodynamics and buoyancy effects.

In contrast, Stonefish is a more recent simulation framework, formally introduced in June 2019 at the MTS/IEEE OCEANS Conference in Marseille (Cieślak, 2019). Stonefish addressed the limitations of earlier tools by providing an accurate simulation of underwater robot dynamics, including full hydrodynamic modeling of vehicle-manipulator systems with support for contact and force sensing. It features a modern rendering pipeline capable of producing realistic underwater environments and supports integration with external software tools and the Robot Operating System (ROS). These capabilities make it particularly well-suited for researchers developing control, perception and navigation algorithms in underwater robotics.

4.1 Simulation Architecture

The simulation environment used in this project is built upon the Stonefish framework. The environment was structured using a ROS-based architecture, integrating core modules for perception, state estimation, navigation, and control.

There are four main functional groups of core nodes that enable high-fidelity operation of the simulation environment (Figure 10).



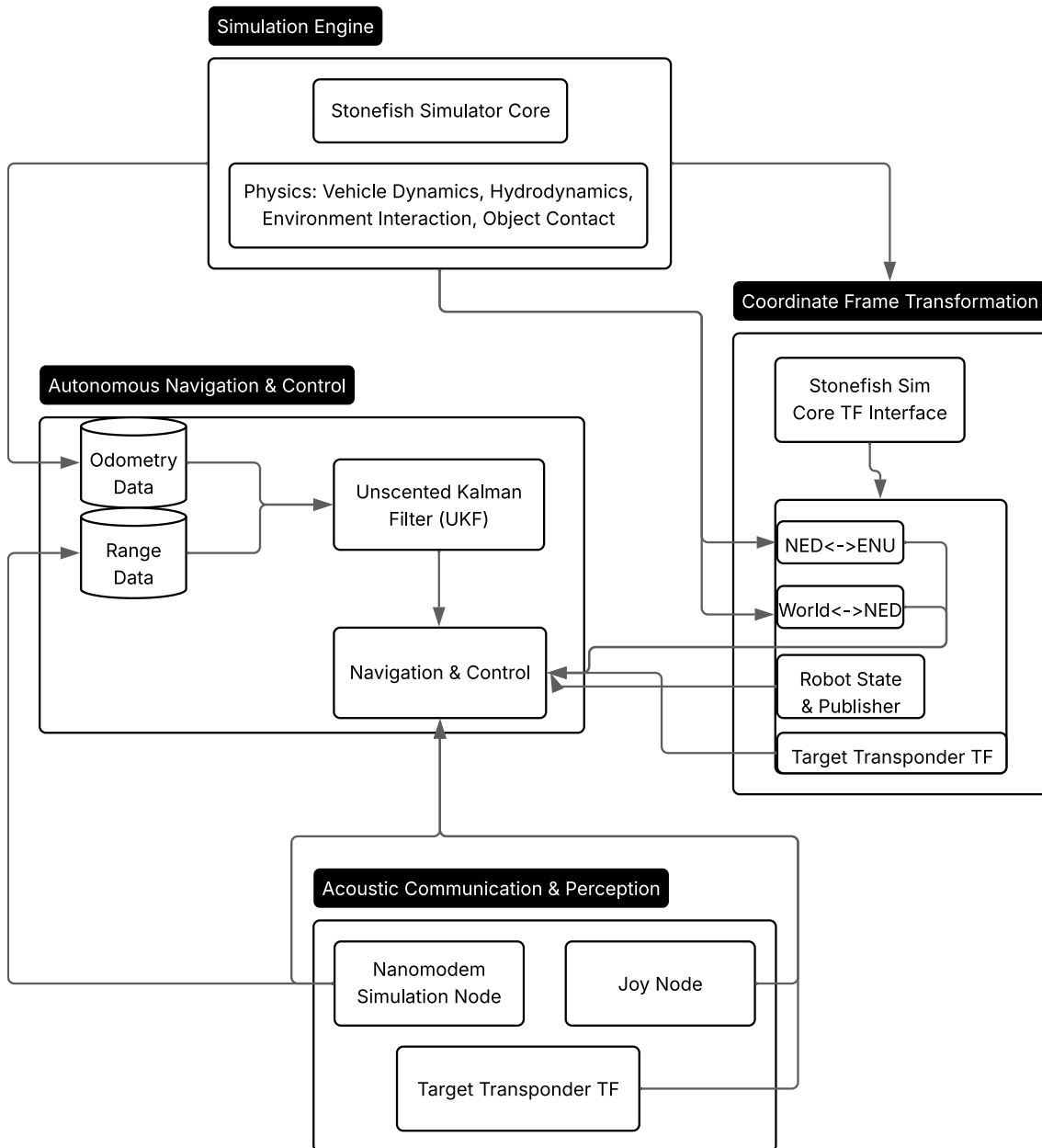


Figure 10. Simulation architecture

The first group is centered around the primary simulation engine, responsible for executing the core physical processes of the environment, including vehicle dynamics, hydrodynamic modeling, environmental interactions and object contact simulation.

The second group is built around the ROS TF package, which plays a critical role in managing coordinate frame transformations across the system. The TF tree maintains a spatial relationship between frames over time, allowing consistent transformation of points, vectors and poses between reference frames. In this setup, the TF tree is populated by the following nodes:

- NED to ENU: Converts data between North-East-Down and East-North-Up coordinate systems.
- World to NED: Establishes the relationship between the global world frame and the NED frame.
- Robot State and Pose: Publish static and dynamic transformations for the AUV's base frame, sensors and manipulator arms.
- Target Transponder TF: Broadcasts the transform of the target transponder to the rest of the system.
- Stonefish Simulator Core: Interfaces with the TF system to anchor simulated objects within the global environment.

The third group is state estimation and autonomous navigation, which includes the nodes for estimating the position of the acoustic tag from the perspective of the AUV and executing autonomous navigation toward that location. The position estimation is performed using a Kalman Filter, specifically an Unscented Kalman Filter (UKF), which processes two main data sources:

- Range data obtained from the acoustic locator system, from the left and right locator devices mounted on the AUV.
- Navigation data generated by the AUV's onboard odometry system.

The UKF uses this information to produce a robust estimate of the acoustic tag (transponder) position within the environment. Once the tag's location is inferred, this estimate is used to compute control commands that guide the AUV toward the target. The guidance system interacts with the simulated thruster system to execute these commands, interpreting velocity directives and converting them into appropriate actuation signals.

These control signals are then handled by the thruster allocation module, which translates the commands into individual thruster efforts, enabling the AUV to autonomously and dynamically approach the transponder within the simulated underwater environment.

The last group is related to communication and perception, where it handles underwater stimulation and perception mechanisms that support the detection phase of ALDFG. There are two primary nodes:

- Acoustic Locator Simulation Node, which is responsible for the functionality of a real world acoustic locator, enabling the exchange of acoustic messages, range measurements and communication between the transponders located on the AUV and



the one positioned underwater. It plays a central role in the detection pipeline by providing the ranging data needed for localization.

- Target Transponder TF: is responsible for broadcasting the spatial transform of the acoustic beacon within the TF tree, allowing other components of the system to localize and interact with the target in the global reference frame.

In addition, manual navigation of the AUV can be performed via the Joy node, which enables teleoperation through a joystick or other input device. This is particularly useful for system testing, manual intervention, or validation in scenarios that require operator control.

4.2 Simulation Setup

When the simulation is launched, the target transponder's location can be freely selected, allowing the user to place it either on the seafloor or within the water column, depending on the intended testing scenario. By default, the vehicle starts at the surface within the reference frame.

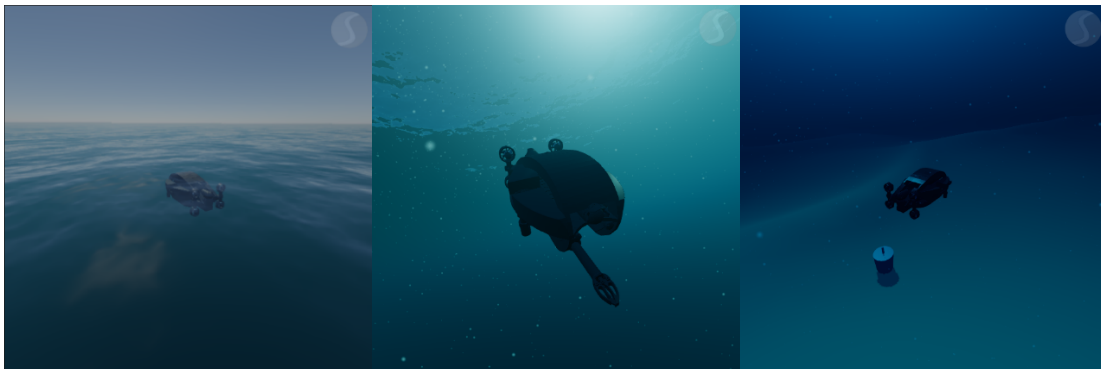


Figure 11. 3D visualization of an approach maneuver in simulation

In this simulation (Figure 11), the primary objective is to replicate acoustic communication between two distinct sets of devices. The locator system on the AUV consists of two separate devices. These transponders emit periodic acoustic signals at a frequency of 1 Hz, staggered in time to avoid overlapping. On the other end, the target transponder acts as a passive listening device, continuously monitoring incoming acoustic pulses. Upon detecting a signal transmitted from one of the vehicle's modems, the transponder immediately issues a response. The time delay between the sent and received signals is then used to compute the range between the vehicle's locator and the underwater acoustic tag, forming the basis for acoustic localization.

5 Automated Robotic Localization and Approach Manoeuvre

Given the simulation setup, both the range measurements between the AUV and the target transponder, as well as the AUV's own odometry data, are available in real time. The range data is derived from the time-of-flight of acoustic signals between the vehicle's modems and the target transponder, while the odometry provides continuous estimates of the vehicle's position and motion within the global reference frame. Together, these two sources of information form the foundation for acoustic-based localization and navigation in the simulated environment.

For localization and navigation in underwater environments, several tools and techniques are commonly used. Among these, Kalman Filters and their variants provide robust state estimation for dynamic systems by fusing noisy sensor measurements. In particular, the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are well-suited for nonlinear models typical of underwater robotics.

Another approach is the use of Particle Filters, which are recursive Bayesian estimators that represent the state distribution using a set of discrete particles. Particle filters are especially useful in environments with significant nonlinearity or uncertainty, where Gaussian assumptions may not hold.

More direct methods, such as trilateration or multilateration, can also be used to estimate position based on distance measurements from multiple known points. However, these methods are particularly sensitive to noise and may produce unreliable results without additional filtering.

In more complex or unstructured environments, Simultaneous Localization and Mapping (SLAM) techniques are often applied, as they enable an autonomous vehicle to build a map of an unknown environment while simultaneously estimating its own position within that map, making it a powerful tool for navigating dynamic or previously unexplored underwater scenarios.

5.1 Multilateration

For the multilateration process, a closed-form algorithm was developed to estimate the 3D position of an unknown target using at least four reference points with known coordinates and their respective distance measurements to the target. The method involves solving a system of nonlinear equations, which can be linearized and resolved through least squares techniques.



The multilateration function accepts as input a set of known 3D coordinates, which is the position of the AUV and associated scalar distances from the position that the vehicle is at the waypoint to the unknown target. Using this dataset, the algorithm aims to determine the fixed position of the beacon by solving a geometric problem, which is to find the point in space that is at the given distances from each known AUV position (see Figure 2).

Mathematically, the multilateration process involves subtracting the squared distance equations for each measurement point with respect to a reference, which in this case is the first waypoint on the list, to eliminate nonlinear terms. This transforms the problem into a linear system of the form $A \times x = b$, where A is constructed from the differences between the AUV positions and b from the range differences.

To solve this, at least 4 measurements must be available, which requires the use of the Householder QR decomposition with column pivoting, a numerically stable method for solving overdetermined linear systems, by reordering columns of A during decomposition based on their norm.

This method already accounts for irregularly distributed AUV's positions or when some measurements carry noise. The final is an estimate of the gear's location, given by vector x , which can be fed to the Kalman filter that is going to be approached in the following section.

5.2 Unscented Kalman Filter (UKF)

In underwater robotics, accurate localization is a critical requirement for autonomous navigation and perception. Given the noisy nature of underwater acoustic signals and the non-linear dynamics of the environment, traditional filtering techniques often fall short of accuracy or robustness. In this project, the Unscented Kalman Filter (UKF) for estimating the position of an acoustic transponder relative to the AUV was implemented, using range measurements and odometry data.

The main goal of the filter is to estimate the 3D position of the acoustic transponder, based on the range measurements from the acoustic locator on the AUV and the AUV's own odometry. The system is nonlinear due to the spherical nature of the range observations and the relative motion of the vehicle.

To cope with nonlinearities, UKF uses a deterministic sampling technique known as the Unscented Transform (UT). This method approximates the distribution of a Gaussian Random



Variable (GRV), by a chosen set of sigma points, which are propagated through the non-linear system to capture the posterior mean and covariance to the third order, for any nonlinearity.

There are 6 main steps of the filter's functioning: initialization, sigma point generation, weights assignment, prediction step, measurement update, Kalman gain, and update.

- Initialization establishes the initial conditions for the filter, including the state vector, covariance matrix, process noise, and measurement noise. At this stage, the multilateration method plays a key role, as the estimated target position obtained through this technique is used to initialize the target's state in the filter. Providing this initial estimate prevents the filter from starting blindly, offering a meaningful starting point that improves convergence toward the true target location. This also enhances the filter's ability to reject outliers and stabilize the estimation process from the outset.
- Sigma Point Generation includes the generation of a set of $2L+1$ (L is dimension) sigma points around the current estimate, to capture the spread and shape of the current state distribution.

$$x_0 = \bar{x} ; \lambda = \alpha^2(L + \kappa) - L$$

$$x_i = \bar{x} + \left(\sqrt{(L + \lambda)P_x} \right)_i, i = 1, \dots, L$$

$$x_{i+L} = \bar{x} - \left(\sqrt{(L + \lambda)P_x} \right)_i, i = 1, \dots, L$$

In the first equation $\lambda = \alpha^2(L + \kappa) - L$, λ is a scaling parameter that determines how far the sigma points are spread around the mean state $\bar{x}$. α controls the overall spread of sigma points around the mean. It's typically set to a small positive value (1e-3) to keep the sigma points close to the mean. κ is a secondary scaling parameter, often set to 0 or 3-L. It influences the weight of the central sigma point and can be used to finetune the spread. β encodes prior knowledge about the distribution of the state. For a Gaussian distribution, β is typically set to 2, which is optimal for capturing the true posterior mean and covariance when the state distribution is Gaussian.

These parameters are responsible for defining how the sigma points are positioned relative to the current estimate and how much influence each one has in approximating the true state distribution after passing through a nonlinear function.

Not all the sigma points contribute equally to representing the true state of the acoustic transponder. Some sigma points are more representative of the underlying distribution than others. Each sigma point is assigned a weight that determines its contribution to the predicted

mean and covariance. These weights are computed based on the spread and scaling parameters of the filter.

- Weights assignment to each sigma point are performed as:

$$w_0^{(m)} = \frac{\lambda}{L + \lambda}$$

$$w_0^{(c)} = \frac{\lambda}{L + \lambda} + (1 - \alpha^2 + \beta)$$

$$w_i^{(m)} = w_i^{(c)} = \frac{1}{2(L + \lambda)}, i = 1, \dots, 2L$$

These sigma vectors are propagated through the system's nonlinear transition function using the Unscented Transform (UT). This process approximates the effect of the nonlinear transformation on the state distribution. Each sigma point $x_i^{t|t-1}$ is computed as:

$$x_i^{(t|t-1)} = f(x_i^{(t-1)})$$

where $f(\cdot)$ represents the nonlinear process model.

Once the sigma points are transformed, the predicted mean $\bar{x}^{(t|t-1)}$ and covariance $P^{(t|t-1)}$ of the state are computed as a weighted sample mean and covariance over the transformed sigma points:

$$\bar{x}_{t|t-1} = \sum_{i=0}^{2n} w_i^m \cdot x_i^{(t|t-1)}$$

$$P_{t|t-1} = \sum_{i=0}^{2n} w_i^c \times (x_i^{t|t-1} - \bar{x}_{t|t-1})(x_i^{t|t-1} - \bar{x}_{t|t-1})^T + Q$$

With the prediction step complete, the update phase begins. The first step is to project the sigma points into the measurement space using the nonlinear measurement function $h(\cdot)$, which models how the sensor perceives the state:

$$Z_i = h(x_i^{(t|t-1)})$$

Each projected sigma point Z_i represents a possible measurement outcome, given the corresponding predicted state of the sigma point. Using these, the predicted measurement mean $\bar{z}_t$ is computed as a weighted sum of the sigma points in the measurement space:

$$\bar{z}_t = \sum_{i=0}^{2n} w_i^m \cdot Z_i$$

Next, the measurement covariance, S_t is estimated to capture the expected uncertainty in the measurement prediction. This is calculated as:

$$S_t = \sum_{i=0}^{2n} w_i^c (Z_i - \bar{z}_t)(Z_i - \bar{z}_t)^T + R$$

R consists of the measurement noise covariance matrix, accounting for uncertainty in the sensor observations, reflecting the noise in the distance measurements between the AUV and the acoustic target transponder, as provided by the locator system. Uncertainty in the vehicle's own odometry is already incorporated during the prediction phase through the process noise model.

The cross-correlation matrix is computed to capture the relationship between the predicted state variables and the predicted measurements. It quantifies how uncertainties in the state influence the uncertainties in the expected measurements. Using this cross-correlation, the Kalman gain is derived as a weighting factor that balances the trust between the predicted state and the new measurement. The Kalman gain determines how much the predicted state estimate should be adjusted based on the innovation parameter, between the predicted and actual measurements. In essence, it ensures that the state update is optimally influenced by the incoming sensor data, considering both the prediction uncertainty and the measurement noise (Wan & van der Merwe, 2000).

$$T_t = \sum_{i=0}^{2n} w_i^c \left(x_i^{(t|t-1)} - \bar{x}_{t|t-1} \right) (Z_i - \bar{z}_t)^T$$

$$K_t = T_t \cdot S_t$$

6 Simulation Tests and Validation

The objective of the simulation tests is to validate the accuracy of the Unscented Kalman Filter (UKF) in estimating the position of an underwater transponder using acoustic range measurements, and to demonstrate the AUV's ability to navigate toward the detected position. During operations, the AUV estimates the tags's position at a frequency of 2Hz to ensure robustness against possible target movement. Although the transponder remains stationary in the simulation environment, real-world conditions may introduce slight drifts in its position due to underwater currents or the mooring dynamic response of a typical planar net under various wave-current combinations. The UKF is designed to accommodate such variations through continuous estimation, providing resilience in both simulated and practical conditions (Xie, et al., 2023).

6.1 Simulation Tests

As previously discussed in Chapter 4, the simulation trials were conducted using the Stonefish simulator. An underwater environment was created, and the physical structure of the AUV, along with its sensor configurations, was defined using a URDF file based on XACRO macros. This file specifies the vehicle's joints, sensor placements (including IMU, DVL and multibeam sonar) and thruster configuration. It serves as the foundation for spawning the AUV model within the Stonefish simulation environment.

With the simulation environment and vehicle model properly set up, it was evaluated the performance of the Unscented Kalman Filter (UKF) and multilateration process in localizing the underwater transponder and guiding the AUV's navigation.

In this chapter, a trajectory will be demonstrated first using only the UKF and another using the fusion between the multilateration process and the UKF.

6.1.1 *Simulating UKF Only*

When the UKF is used alone, it typically initializes the target's position either at the origin or at a random location. This often introduces significant errors, particularly in the estimation of the depth (z-axis). To address this issue, two complementary strategies were implemented. The first involves the AUV performing a square-shaped trajectory at the surface to acquire an initial estimate of the target's location in the horizontal (XY) plane. However, this approach provides only a rough approximation. To refine the estimate, a second strategy is applied in which the

AUV follows a conical spiral trajectory centered around the preliminary estimate, progressively closing in on the target using real-time distance measurements.

As shown in Figure 12, the UKF initially estimates a position far from the actual location of the target. It begins to yield useful data only after the surface-level square trajectory, estimating the target's position around coordinates (-6, 8, 0). From this point, the AUV initiates the conical trajectory, adjusting its path based on updated distance readings. The mean of this spiral narrows dynamically as the AUV descends, bringing the vehicle closer to the true target location and improving convergence of the UKF. As the AUV approaches the target, both the depth and radius of the conical path decrease.

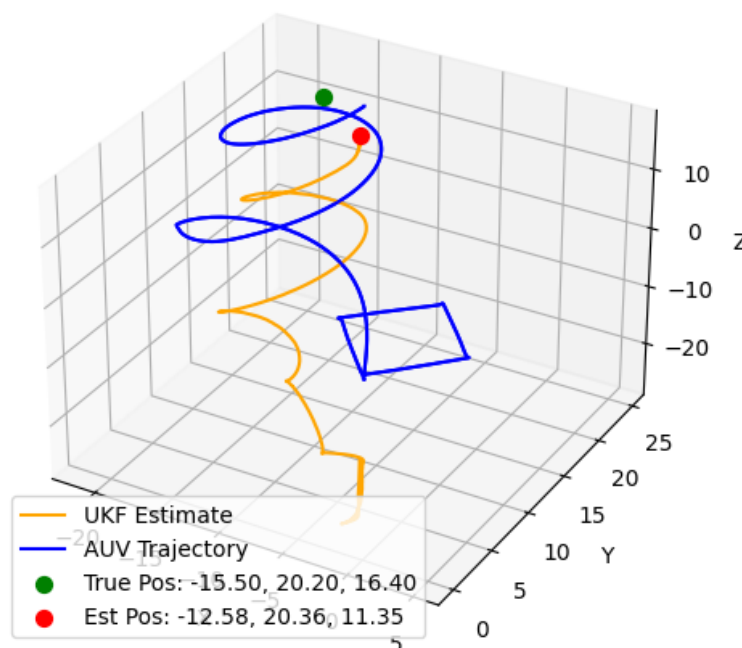


Figure 12. Conical-shaped trajectory- Simulation

Ultimately, the AUV achieves a strong convergence in the XY plane, with the final estimated position closely matching the true target location, within an error of 5.8 meters. Although the z-axis estimation remains less accurate, however the designed approach minimizes its impact, as the descending motion of the AUV compensates for this limitation, ensuring successful target localization and potential retrieval.

6.1.2 Multilateration + UKF

The second method proposed for the autonomous localization and approach of the target involved combining a multilateration algorithm to produce an initial position estimate. This estimate provided approximate (x, y, z) coordinates of the target, which were then used to initialize the UKF.

In ideal conditions, where there is no acoustic signal noise or odometry data loss, the multilateration method alone could accurately determine the target's position. However, in practical scenarios, communication noise and data dropouts are common and can accumulate, leading to significant position estimation drift over time.

In the simulation setup, odometry data remained accurate, but acoustic communication was subjected to a 2 meter noise factor. Under these conditions, the multilateration algorithm estimated the target's position at approximately (-15.27, 16.29, 13.86). While reasonably close, this estimate was still around 5 meters from the true target position, which can be problematic in turbid waters where onboard cameras struggle to detect objects beyond 4 meters.

To overcome this, the UKF was initialized using the multilateration estimate, enabling the filter to refine the position more precisely, particularly in the z dimension. The AUV then executed a direct trajectory toward the estimated target location, continuously correcting its path using the UKF output. As a result, the AUV successfully approached the target, achieving a final offset of only 0.56 meters. Notably this approach greatly improved depth estimation, reducing the z error from 5 meters to just 4 centimeters.

These results are shown in Figure 13 and Figure 14, where the green lines represent the triangle-shaped path from the multilateration process and the blue line the trajectory of the AUV using the UKF data.



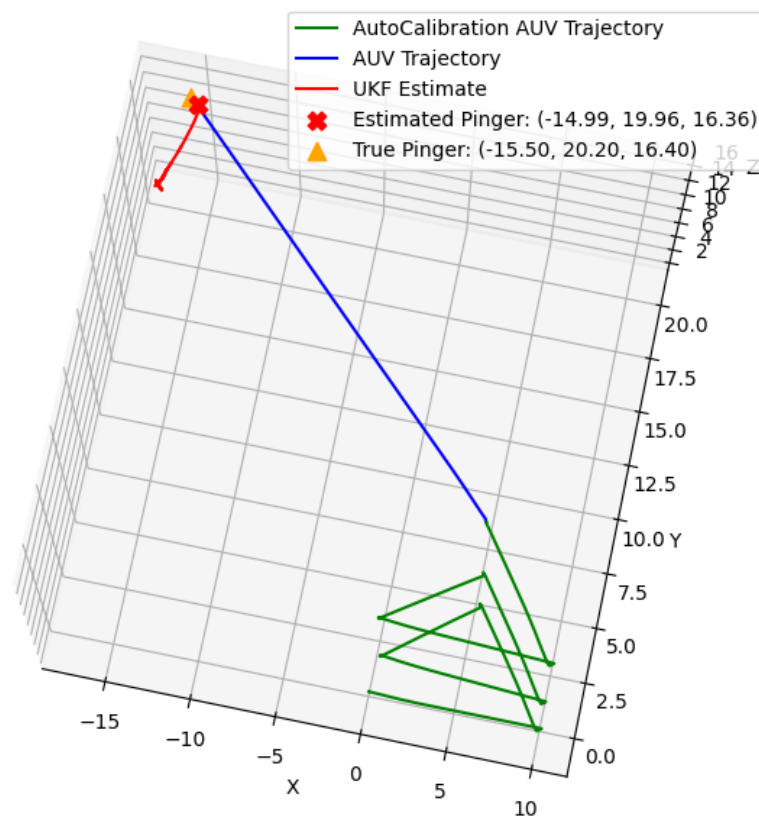


Figure 13. Multilateration with UKF- Simulation 1

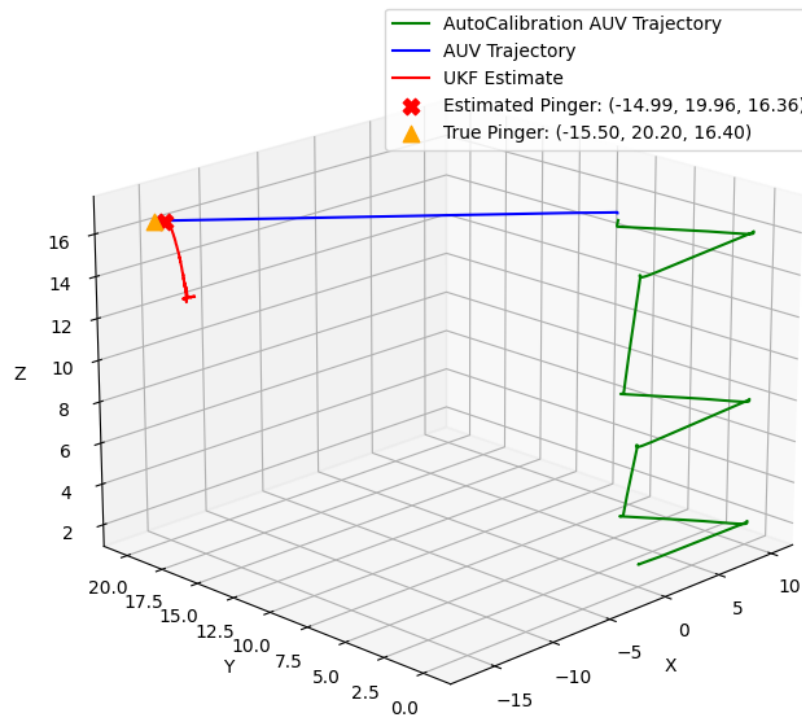


Figure 14. Multilateration with UKF- Simulation2

7 Field Tests and Results

Field tests were conducted at Leixões Harbor, a coastal location that offers a controlled environment due to its proximity to shore and shallow depths not exceeding 20 meters, which is particularly advantageous in the event of navigation issues, as it facilitates easier retrieval of the AUV if necessary (Figure 15).

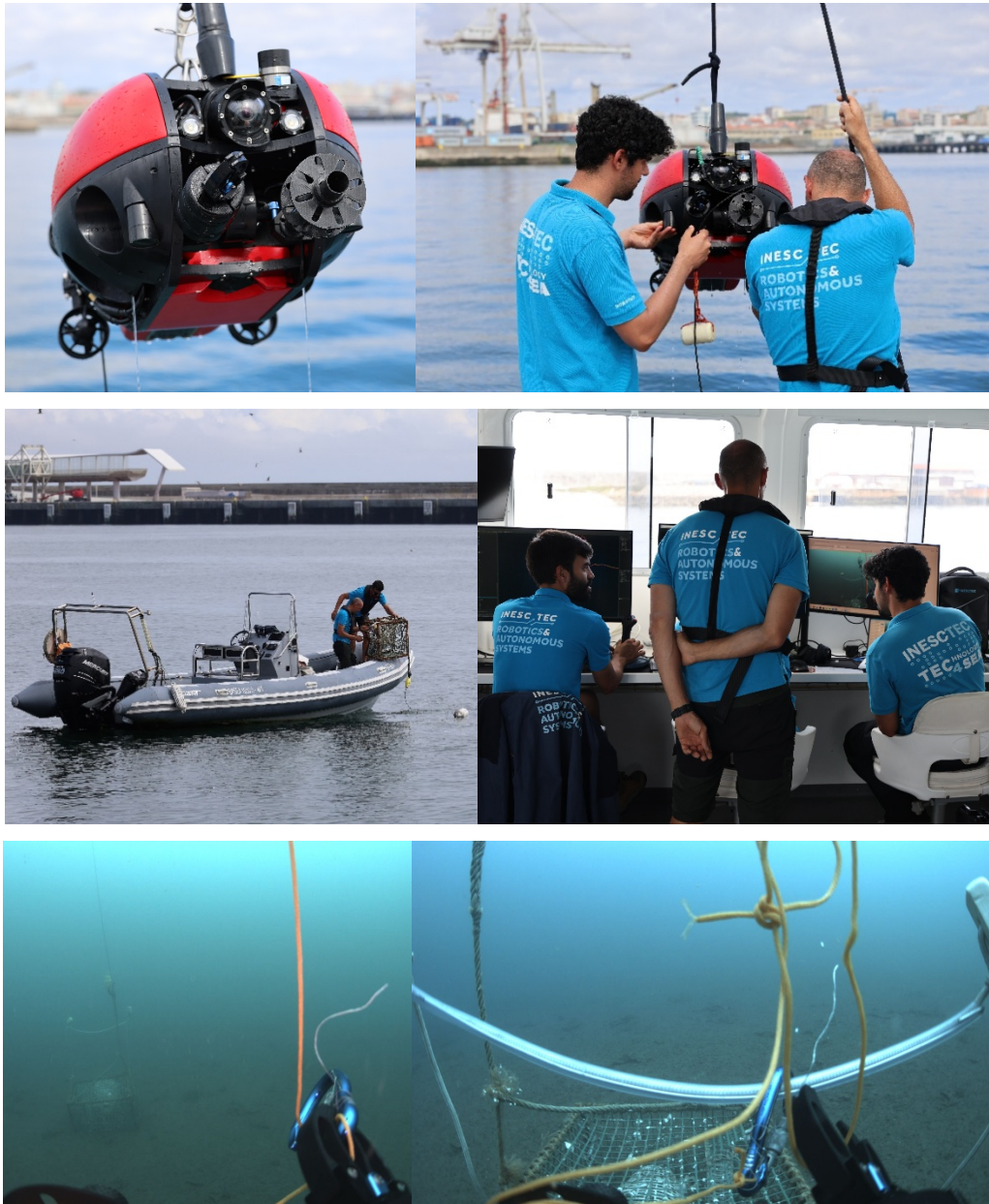


Figure 15. Field tests at Leixões Harbor – Deployment of IRIS AUV and ALDFG, onboard operations, detection, and attachment to ALDFG

For the field tests, a triangular-shaped trajectory was also applied for the multilateration process, consistent with the approach used in the simulation chapter. However, the execution of the trajectory in real-world conditions differed notably. Each vertex of the triangular path was approached vertically, as the triangles were aligned along the vertical axis. The AUV descended vertically to a vertex at a depth of 16 meters, then ascended along the same XY coordinates. Upon surfacing, it moved horizontally—where GNSS-based RTK positioning was available—to the next vertex, repeating the process for the remaining points.

Unlike in simulation, where odometry data remained uninterrupted and ideal conditions were assumed, real-world environments, particularly in GNSS-denied zones, are prone to odometry drift and signal loss. This vertical approach was specifically designed to address such challenges. By constraining horizontal movement to surface intervals where precise GNSS data is available, the method minimizes positional uncertainty between trajectory points and improves the reliability of the multilateration input data.

Figure 16 presents the outcomes from the field tests. Initially, the multilateration method resulted in an estimated position with an error of approximately 6 meters. After applying the filter, this error was reduced to around 2 meters. The red trajectory, representing the filter's position estimates over time, exhibits a noticeable drift caused by a few out-of-range distance measurements. These inaccuracies led to a significant deviation along the z axis, though the filter eventually reconverged to the transponder's true location.

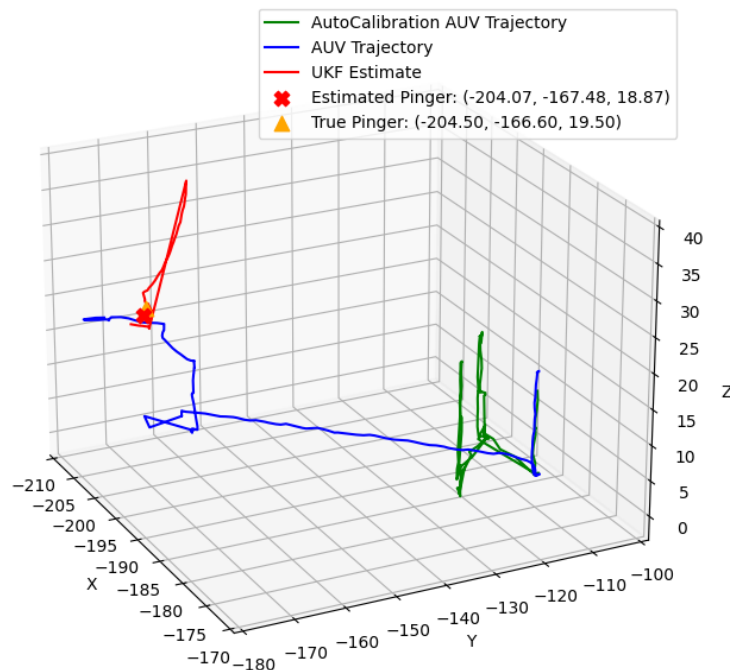


Figure 16. Multilateration with UKF- Field tests

This behaviour illustrates the challenges of relying on direct localization methods in real-time. Even minor deviations in odometry or range data can lead to substantial errors in position estimates. As such, robust filtering techniques are essential for mitigating these effects.

The IRIS robot deployment and operation from a fishing vessel was tested in an operational scenario with fisher boats from Patti, Italy (Figure 17, Figure 18, Figure 19).



Figure 17. Fishing vessel from Patti fishing community during NETTAG+ field experiments at sea



Figure 18. Loading of the IRIS robot into the fishing vessel with the help of a small pulley



Figure 19. IRIS AUV deployment and operation from a fishing vessel

The low vehicle weight (around 30kg) and dimensions allowed for easy operation from a coastal fishing vessel. Successful deployment and recovery operations of the robot were performed.

A representative fishing net (Figure 17) was deployed with acoustic tags and upon field tests with the surface locator unit operating from another fishing boat (the one carrying the robot), the robot was deployed. Using its onboard tag acoustic locators the vehicle approached the tagged gear up to a distance of less of 10m. Final approach and attachment were not possible to be performed in this field trial due to a mechanical failure in one of the rear forward thrusters.

8 Conclusion Remarks

This report focused on the challenge of autonomously locating and approaching lost fishing gear fitted with acoustic tags in underwater environments. By developing a combined approach using multilateration and UKF, the system sought to enhance the localization accuracy of tagged objects while accounting for realistic environmental conditions and sensor-related limitations.

Initial simulation results demonstrated the feasibility of using multilateration to estimate an approximate position of the target, particularly when accurate odometry data was available. However, field tests revealed that multilateration alone can result in significant estimation errors, up to 6 meters, mainly due to acoustic noise, limited range measurements, the lack of vision from a sensor when the target is displaced in the opposite direction, and odometry drift in GNSS-denied environments. To attenuate this problem, a filtering process with UKF is applied, which is initialized with the estimated value from the multilateration process. The filter effectively minimized the final localization error to about 2 meters, enabling the use of imaging cameras in turbid waters to guide the claw system in attaching to the gear.

A challenge was noted in the field due to a drift in the UKF's z-axis estimate, caused by a series of out-of-range distance measurements.

Despite this, the UKF was able to reconverge toward the true position of the transponder, demonstrating the robustness of the filtering method. These results emphasize the importance of combining multiple techniques, such as range-based localization and state estimation filters, since the UKF without a proper initialization wouldn't converge so easily and accurately as in this case.

The trajectory in these situations also plays a key role in data quality. In both simulated environments and field tests, a triangle trajectory was adopted. However, in the field tests, the trajectory had to follow a different course, as it was based on a vertical type of motion, allowing for the AUV to surface consistently to receive GPS position data. This method helped counteract the absence of GNSS, mitigating the problem of odometry information loss.

In conclusion, while the proposed system proved effective in narrowing the localization error of tagged gear, the results also highlight the limitations of current sensors in complex underwater conditions.

A simple mechanical device for marking the location of lost gear was developed and integrated into the IRIS robot. This device consists in an attachment hook to the gear, and marker/pulling

line and a small floater. The robot attaches the line to the gear with the supervision of a human operator and releases the line that can then be further used to retrieve the gear. This system was validated in recovery fishing traps during sea trials.

The existing multipurpose gripper can also be used to pick up objects from the sea floor. For ALDFG its use in the recovery process is limited to weight limitations due to the limited carrying capacity/thrust of the robot. This gripper can also be equipped with a cutting device, allowing for underwater cutting of small lines or fishing gear to help the retrieving process.

The developed mechanical retrieval support systems and autonomous approach control manoeuvres demonstrated the supporting capabilities of the robot in aiding the location of tagged gear and also in the recovery process.

Although validated in the field, further testing and operation at sea, and in particular with the cooperation of participant fishermen, is still required to extend and benchmark the use of the system with multiple fishing gear types and in very diverse conditions of operation at sea.



9 Bibliography

- Cieślak, P. (2019). "Stonefish: An Advanced Open-Source Simulation Tool Designed for Marine Robotics, With a ROS Interface," . *OCEANS 2019 - Marseille, Marseille, France,,* 1-6.
- Cruz, N. A., Matos, A. C., Almeida, R. M., & Ferreira, B. M. (s.d.). *Dart- A Portable Deep Water Hovering AUV*.
- Ritchie, H., Samborska, V., & Roser, M. (2023). *Plastic Pollution*. Obtido de OurWorldinData.org: <https://ourworldindata.org/plastic-pollution>
- Wan, E. A., & van der Merwe, R. (2000). *The Unscented Kalman Filter for Nonlinear Estimation*. Beaverton, Oregon: Oregon Graduate Institute of Science & Technology.
- Xie, M., Mu, Y., Wei, Y., Xu, T., Sun, Z., & Yuan, C. (2023). Experimental investigation on the mooring dynamics of the flexible trash intercept net under wave-current combined actions. *Ocean Engineering*, 113544.