# Unmanned Marine Vehicle Cooperative Offshore Infrastructure Monitoring with Multimodal Underwater Feature Transmission

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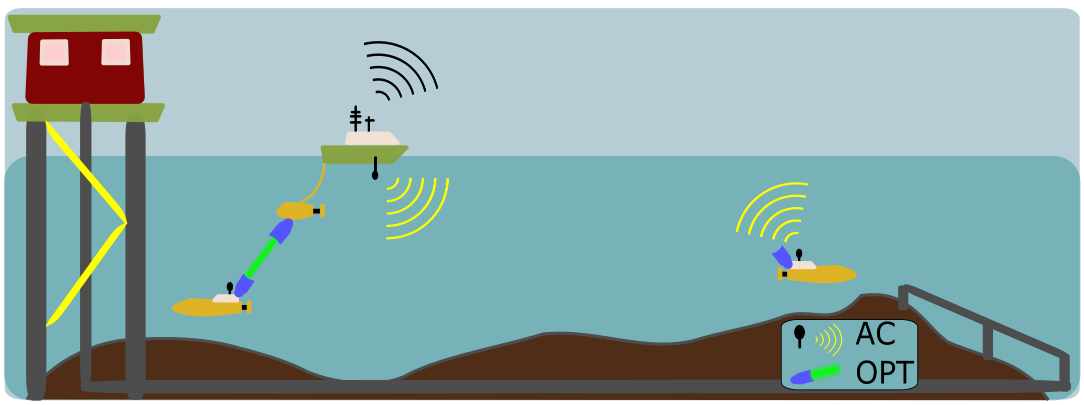


**Figure 1: ASV and AUVs coordinated mission to detect anomalies in offshore infrastructures.**

## ABSTRACT

Cooperation between Autonomous Underwater Vehicles (AUVs) and Autonomous Surface Vehicles (ASVs) can greatly enhance their usefulness in wide-area underwater monitoring tasks for critical infrastructure such as offshore pipelines. The AUVs can provide a close-up view of the pipeline and physically interact with it if any maintenance is needed, while the ASV can act as an offloading platform for complex computational tasks that are beyond the capabilities of AUV on-board hardware. However, the communication requirements are significant, and the harsh underwater propagation environment requires an ASV to move close to AUVs when they need assistance. In this work, we propose the Interactive Error Resolution (IER) scheme, which combines multimodal communication and subsequent interaction rounds to significantly reduce false alarms, reducing the mission time and the system's energy consumption. We found that the proposed IER protocol outperforms the naive Strict Error Response (SER) approach by an order of magnitude in terms of mission time and energy consumption, significantly improving the effectiveness of the AUV-ASV team in the pipeline monitoring task.

## CCS CONCEPTS

• **Networks** → **Network simulations**; **Network performance analysis**; Peer-to-peer protocols.

## KEYWORDS

AUVs, multimodal underwater networks, DESERT Underwater, underwater communications


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## 1 INTRODUCTION

Over the last few decades, underwater operations have gained significant popularity and are increasingly important in both civil and military activities. Among the various applications in this field, the inspection of underwater pipelines used for oil, gas, and fluid transportation stands out. Given the harsh conditions they are subjected to, regular assessment and monitoring of these pipelines is of the utmost importance to ensure safe transportation [1].

The use of Autonomous Underwater Vehicles (AUVs) has proven to be highly effective in addressing this mission, yielding positive results in both industrial and research activities [1]. AUVs are compact in size and equipped with intelligent control systems, sensors, cameras, and automatic navigation and localization systems. Compared to cable-controlled Remotely Operated Vehicles (ROVs), AUVs are generally easier, faster, and more cost-effective to operate, making them suitable for long-range missions. Cameras and other light-sensitive sensors can be mounted on each AUV to enable a close-by visual inspection of pipelines, as they are highly capable of surveying underwater sites and can closely approach targets. However, the computational power of AUVs is often quite limited due to the restrictions on their hardware, and complex filtering or even learning-based models are often beyond their capabilities. The monitoring task might require complex or even learning-based models [1] due to the presence of noise and other disturbances, making AUVs alone unsuitable for reliable monitoring of the infrastructure. For this reason, we can harness the much higher computing power, communication capabilities, and mobility of Autonomous Surface Vehicles (ASVs) to provide guidance to multiple AUVs operating on the seabed.

AUV-ASV cooperation has been studied and applied in various scenarios. For instance, a model in which ASVs process the data collected by a swarm of AUVs, moving on the surface according to the communication requirements of the AUVs, was proposed in [17]. This concept has also been successfully applied to coral monitoring [18] and mine search [9]. However, its benefits have never been exploited in pipeline monitoring.

Mission coordination between AUVs and ASVs requires a stable and reliable communication link. In contrast with the terrestrial scenario, the use of radio frequency communication devices is mostly restricted to docking applications [5], due to the severe attenuation of the underwater electromagnetic channel. Optical communication, instead, can enable high rate links with capacities on the order of a few megabits per second at a range of a few tens of meters. Nowadays, it is the most common broadband communication technology, but requires alignment between transmitter and receiver and is affected by turbidity and sunlight noise [20]. Finally, acoustic communication is the most widely used communication technology in the underwater scenario. Acoustic waves, in fact, can propagate for several kilometers, at the cost of a very small bandwidth and a low datarate, on the order of a few kilobits per second [13].

Research on the communication limits of these approaches has been minimal so far: pipeline infrastructures can cover large areas, and deploying a significant number of ASVs is not practical due to their significantly higher component and operational costs. In this context, an intelligent adaptive approach can manage to limit the risk of interference and collisions by transmitting as little as possible, while still making well-informed decisions to limit the movements of the ASVs and, consequently, their energy expenditure.

In this work, we propose a model for AUV-ASV cooperation that exploits multimodal optical and acoustic communication to improve task performance, minimize mission time, and avoid useless energy consumption. The scenario is shown in Fig. 1: the AUVs roam the bottom and follow the pipeline, visually inspecting it for anomalies and potential issues [2]. If an anomaly requires maintenance operations [7], the ASV then moves to that location and lowers a small ROV to be within 10 meters of the AUV[1]. This establishes a short-range, high-bandwidth optical link with the AUV to further inspect the damage, obtaining a detailed scan that can aid in planning for future maintenance interventions. However, false alarms are time-consuming, as they require the AUV to wait for the ASV and perform the detailed scan, and energy-intensive, as the ASV needs to physically move. We then consider an iterative decision process that can help reduce false alarms: whenever an AUV detects a potential anomaly, it transmits a compressed image to the ASV through its long-range acoustic modem, then waits for a reply. If the information is sufficient to make a decision, the ASV then either signals a false alarm or moves to the AUV to fix the issue; however, the image might not be enough to make a decision on one side or the other [7]. In these uncertain cases, the AUV then takes more pictures from different points of view and transmits them, providing more elements for the ASV to decide before it starts moving. We consider a realistic simulation in a simple system with a single ASV and 4 AUVs, showing that the proposed adaptive strategy can ensure lower energy consumption and reduce mission duration by significantly reducing false alarms even in this simple case. The proposed Interactive Error Resolution (IER) system outperforms the Strict Error Response (SER) baseline strategy, which considers all possible anomalies as worthy of investigation, with an improvement by an order of magnitude in terms of mission duration and energy efficiency.

The rest of this paper is structured as follows. In Sec. 2, we describe the state of the art. The system model and simulation architecture are presented in Sec. 3 and Sec. 4, respectively. The simulation results are discussed in Sec. 5, and we provide our concluding remarks in Sec. 6.

## 2 RELATED WORK

Detecting targets underwater, whether through computer vision or other technologies, has become crucial for transitioning from ROVs, restricted in their range and movement by the connection cable, to fully untethered AUVs. However, achieving practical and reliable outcomes with computer vision in underwater environments poses significant challenges. Factors such as insufficient light, scattering, absorption phenomena, and other underwater conditions contribute to these difficulties [15].

It is evident that underwater applications of deep learning techniques have not yet attained the same level of success as their surface counterparts, which include tasks like classification, analysis, and segmentation [12], due to the more specialized nature of the

[1]The concept of ASV-carried ROV is well established, and dimonstrated in the RoboVaas project: https://www.youtube.com/watch?v=ZseCsm1kWmE.

task and the limited availability of usable data. Despite these challenges, data-driven methods, particularly those based on deep learning using Convolutional Neural Networks (CNNs), have emerged as the forefront tools for underwater image analysis [15]. It is thus important to consider the energy consumption limitations of deep learning algorithms on AUVs, as they may impose restrictions on their usage, especially during long-duration missions, and other hardware limitations that constrain AUV computational capabilities. Therefore, the development of efficient error recognition algorithms is crucial in order to address these limitations and ensure optimal performance in underwater target detection and analysis tasks.

Researchers are actively exploring various solutions, with the majority focusing on improving algorithms to enhance image quality through deep learning or other methods. Another promising avenue is the collaboration between AUVs and ASVs. Although it has not yet been applied to this specific problem, building upon the results obtained in other projects, this collaborative approach shows great potential. For instance, a smart tactic that quickly rules out or confirms the existence of a target was presented in [17]. In highly suspected areas, ASV and AUV collaborate closely to validate or dismiss the presence of a target, thereby minimizing unnecessary movements for the AUV. This collaborative system achieved a remarkable 25% reduction in searching time and similar total energy consumption savings. A similar approach has been used in [9] for mine detection. In this scenario, ASV mission trajectory is based on sensor data, and at any point during the patrol mission, the ASV can ask the collaborative AUV to perform a close-up identification. The data collected by both vehicles are merged and analyzed to achieve higher precision and reduce mission risks.

The idea considered in this work is to iteratively transmit data from different points of view, so as to disambiguate more difficult cases before the ASV needs to move at all; this reduces false alarms, making the mission quicker and more efficient. This approach takes inspiration from the field of semantic communication [19]: the ASV does not need to take a detailed scan of every location, as it can discriminate whether an anomaly is present with limited data. This type of approach also has significant parallels with the remote source coding problem [10], in which the transmitter has access to observations correlated to an underlying source. The objective is then to infer a random variable correlated with the source signal, i.e., the presence of an anomaly. Joint source and channel coding approaches [3] combine the awareness of the communication medium with the knowledge of which data is needed for a task, but the complexity of the problem requires the use of deep learning networks.

In underwater applications, a heuristic iterative solution that only requires the AUV to gather more observations, rather than optimally compress them based on complex patterns, can overcome computational limitations and provide a simple but solid semantic approach to the cooperative monitoring problem. Another learning paradigm that can be useful to our approach is active learning, in which a learning agent can actively query for more data: this is commonly designed in terms of data points, i.e., asking for new labeled samples to improve the model, but some studies [14] also consider the problem of partial features. These models [8] can be used to request additional features dynamically and only when they are needed, and even considering multiple exit structures for neural

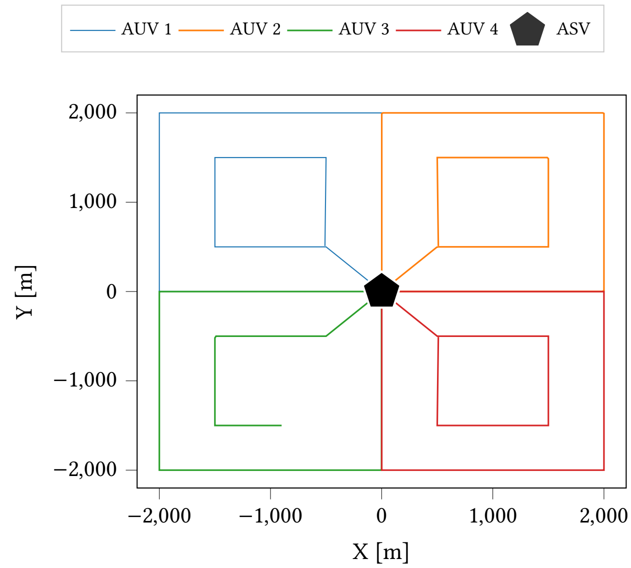


**Figure 2: AUV trajectories in the map.**

networks [24], which may be designed to request the additional features only if the classification with the basic feature set fails.

## 3 SYSTEM MODEL

We consider a scenario with a single ASV aiding 4 AUVs, each inspecting a quadrant of the seabed area. Fig. 2 illustrates the trajectory followed by the AUVs, that are deployed at a depth of 100 m, during a simulation. The ASV initially transmits the mission waypoints, and the AUVs follow a direct line towards the next waypoint. Once reached, they turn towards the next waypoint in the queue. The ASV's initial position is in the center of the map, and it remains stationary until one of the AUVs detects a potential anomaly. If the anomaly is confirmed, the ASV will then proceed to the location of the AUV, where it will lower a small ROV equipped with optical modem to establish a high rate optical link with the AUV. This will allow the AUV to transmit a detailed scan of the anomaly to the ASV, gathering data for future maintenance operations, before going back to its pre-determined monitoring path.

Each AUV moves at a velocity of 0.5 m/s and performs a scan of the infrastructure every 60 seconds. The nature of this measurement can vary based on the specific application being implemented, and our method is fully agnostic to the specific type of measurement. In all cases, the obtained information is subject to a certain level of noise due to water conditions and other disturbances such as marine life or cloud cover. We then expand the most common statistical model of anomalies, which considers the presence of an anomaly to be an independent Bernoulli random variable with probability $\varepsilon$, to extend it to a more general state definition that can simulate the output of error identification algorithms. We consider the continuous interval $[0, 1]$ as a state space, with $x \leq \varepsilon$ if an anomaly is present. We then model the state of each location as an independent random variable $x \sim \mathcal{U}(0, 1)$, drawn from a uniform distribution. In fact, in this scenario, the output is often continuous, instead of binary, to express the confidence level of the solution. The data transmitted from the AUV is then processed by the ASV, obtaining a value $y_1 = x + w_1$, where $w_1$ is an additive Gaussian noise with variance $\sigma^2$. This Gaussian noise represents the errors due to disturbances in the water, and we assume the value of $\sigma$ and $\varepsilon$ to be known to the ASV. This modeling choice is relatively simple, but the use of Gaussian outputs to represent uncertainty is common in Bayesian frameworks for computer vision [11], as Gaussian distributions represent the sum of large numbers of potential disturbances relatively well. The main idea of this work is also relatively robust to different distributions of potential errors, as long as the statistics of the error are known or easy to estimate.

We can then use the value of $y_1$ to compute the estimated state $\hat{x}$, which is equal to $y_1$ if we only have one measurement. If we have multiple measurements, the maximum likelihood value $\hat{x}$ is the mean of the measurements, as they all have the same noise variance. The estimated anomaly probability in that location is:

$$p_e(\hat{x}) = Q\left(\frac{\hat{x} - \varepsilon}{\sigma}\right), \tag{1}$$

where $Q(\cdot)$ is the Gaussian Cumulative Distribution Function (CDF). We can then define a threshold $\theta$ to consider the state to be normal: if $p_e(\hat{x}) \leq \theta$, the ASV decides that there is no anomaly, and the AUV goes to the next location on the map. On the other hand, if $p_e(\hat{x}) \geq 1-\theta$, we can be reasonably certain that there is an anomaly, and the ASV then moves towards the AUV to obtain a detailed scan.

However, there may be a significant gray area: as Fig. 3 shows, when $p_e(\hat{x}) \in (\theta, 1-\theta)$, the ASV is uncertain whether there is an anomaly in a specific location. In the figure, the estimated probability of having an anomaly is low, but we cannot entirely rule it out. We can then consider two methods to resolve the uncertainty, including a classical, more conservative one that will act as a benchmark, and our proposed cooperative error resolution method.

*Strict Error Response (SER).* The SER method takes a conservative approach, basing its decision on the measurement obtained from the AUV: whenever an anomaly cannot be ruled out, i.e., whenever $p_e(\hat{x}) > \theta$, the ASV confirms the anomaly and moves towards the AUV to obtain a detailed scan. In the meantime, the AUV stands still and waits for the ASV's arrival. This method ensures that the probability of undetected anomalies is extremely small, but the ASV must deal with a potentially large number of false alarms.

*Interactive Error Resolution (IER).* The IER method tries to solve the false alarm problem by considering an iterative approach, in which the ASV and AUV cooperate to determine whether the anomaly is present. Whenever the ASV is uncertain, it will ask the AUV for more information. The AUV will then get another measurement from a different point of view and transmit it to the ASV, giving it another data point $y_2$, with an independent noise $w_2$. By taking the maximum likelihood estimation, we have:

$$\hat{x} = \frac{1}{N}\sum_{i=1}^{N} y_i. \tag{2}$$

We can then reduce the variance of the estimate by a $\sqrt{N}$ factor:

$$p_e(\hat{x}; N) = Q\left(\frac{\sqrt{N}(\hat{x} - \varepsilon)}{\sigma}\right). \tag{3}$$

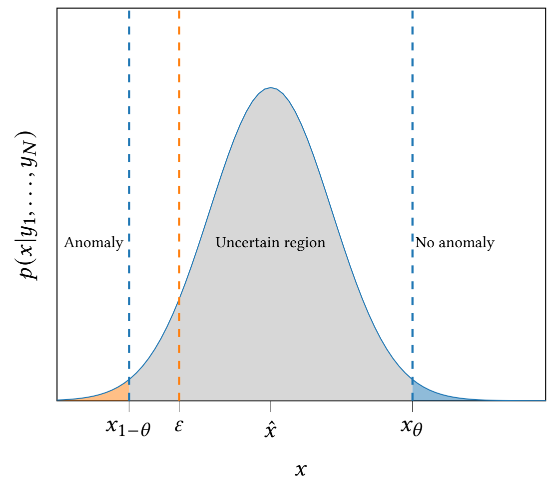


**Figure 3: Error model representation.**

As the absolute value of the argument of the Gaussian CDF tends to increase with the number of measurements, the belief over the anomaly will improve, tending towards either 0 or 1 as the number of measurements grows to infinity. The idea of the IER scheme is then simple: whenever the situation is uncertain, the ASV keeps requesting new packets from the involved AUV until it can definitively rule out the possibility of an anomaly, i.e., $p_e(\hat{x}; N) \leq \theta$, or the anomaly is confirmed, i.e., $p_e(\hat{x}; N) \geq 1 - \theta$. Throughout this operation, the ASV maintains its position and is capable of receiving packets and analyzing data from all four AUVs. Once the anomaly is confirmed, the ASV moves towards the error location to resolve it. Upon reaching its location, the ASV informs the AUV that the error has been resolved. If, after gathering additional information, the ASV decides that there is no anomaly, it informs the AUV, which can then resume moving and continue with the mission.

## 4 SIMULATION SETUP

The system model described above has been implemented using DESERT Underwater [6], an open source underwater network simulator and experimentation framework developed by the University of Padova and publicly available online.[2]

Both underwater acoustic and optical transmissions are simulated. The acoustic transmission is simulated using the model presented in [21]: we assumed a central frequency of 20 kHz and a bandwidth of 10 kHz, with a bitrate of 4.8 kbps. The transmission power was set to 175 dB re 1 $\mu$Pa; we also assumed some faraway shipping activities, a wind speed of 5 m/s, and practical spreading. With this configuration and the model in [21], we ensure that the area depicted in Fig. 2 is fully convered. The underwater optical transmission has been modeled according to [4], assuming transmissions with blue wavelength in coastal water with an attenuation coefficient of 0.4 $\mathrm{m}^{-1}$, a transmission power of 50 W, and a bitrate of 1 Mbps. No sunlight noise is considered, as we assume the mission to take place during the night: with these conditions, the optical range is approximately 13 m. Each simulation lasts 150000 seconds,

[2] https://github.com/signetlabdei/DESERT_Underwater.git

| | |
|---|---|
| UW/AUV | UW/AUV/ERR |
| UW/UDP | |
| UW/STATICROUTING | |
| UW/MULTI_TRAFFIC_RANGE | |
| UW/CSMA_ALOHA | UW/CSMA_ALOHA |
| UW/PHYSICAL | UW/OPTICAL |

**(a) AUV protocol stack.**

| | |
|---|---|
| UW/AUV/CTR | UW/AUV/CER |
| UW/UDP | |
| UW/STATICROUTING | |
| UW/MULTI_TRAFFIC_RANGE | |
| UW/CSMA_ALOHA | UW/CSMA_ALOHA |
| UW/PHYSICAL | UW/OPTICAL |

**(b) ASV protocol stack.**

**Figure 4: Protocol stack of AUV (a) and ASV (b).**

and each AUV follows a predefined set of fixed waypoints. Results are analyzed averaging over 30 simulation runs to obtain statistical accuracy, and presented with the 95% confidence interval. Since packets are transmitted periodically, to avoid synchronized transmissions between AUVs, the random listen time of CSMA-ALOHA used with the acoustic modem is set to be at least as long as the maximum propagation time, i.e., 3.7 s.

The access protocol employed in the system is CSMA-ALOHA, as illustrated in Fig. 4. Additionally, a multitraffic controller has been installed, enabling the system to switch between acoustic and optical transmission based on the distance to the destination device. This ensures that the most appropriate communication mode is used, depending on the proximity of the devices. At the application layer, there is a control application. From the ASV side, this application sends the destination points to the AUVs. On the AUV side, the application manages incoming packets and sets the next destination for the vehicle. Additional application modules, namely Module/UW/AUV/ERR and Module/UW/AUV/CER, have been incorporated into the system. The first module is installed on the AUVs. It initializes the error state and allows the vehicles to resume movement once the error has been resolved. The second module, installed on the ASV, receives and analyzes error packets, computes the estimate $\hat{x}$ and the error probability $p_e(\hat{x}; N)$, and decides the appropriate action based on the type of error and following the IER procedure. In this simulation, we did not consider the ASV model of the scenario, and simply drew a value $y_n$ at each transmission following the noise model from the previous section. We also designed the application modules Module/UW/AUV/ERB

**Table 1: Simulation Parameters**

| Parameter | Value |
|---|---|
| Simulation runs | 30 |
| Duration | 150000 s |
| Period | 60 s |
| UW/AUV - CTR Packet size | 5 B |
| UW/AUV/ERR - CER Packet size | 125 B |
| Anomaly probability $\varepsilon$ | 0.01 |
| Estimation error $\sigma$ | 0.01 |
| AUV number | 4 |
| AUV speed | 0.5 m/s |
| ASV speed | 1.5 m/s |
| Acoustic bitrate | 4800 bps |
| Optical bitrate | 1 Mbps |

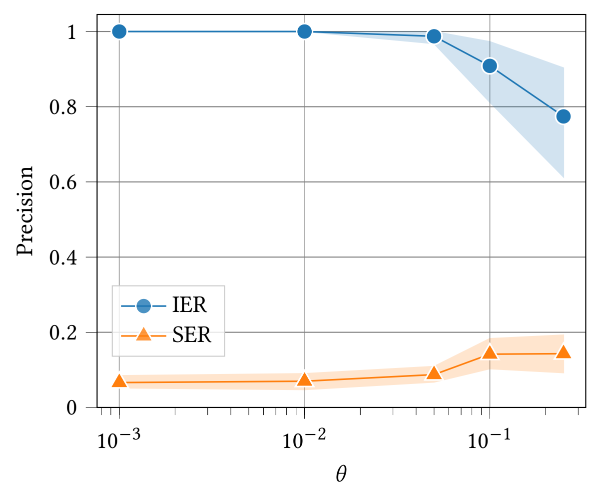


**Figure 5: Precision: number of true anomalies identified divided by the total number of reported anomalies (including false positives).**

and Module/UW/AUV/CEB, which implement the same actions as the previous modules following the SER method instead of IER. A lightweight transport layer, named Module/UW/UDP, ensures that packets are delivered to the correct application, while all nodes are in range: the routing table of the networking module is then trivial, and just sets the next hop equal to the final destination.

# 5 RESULTS

The results of the simulation mentioned above have been collected with a fixed anomaly probability $\varepsilon = 0.01$ and $\sigma = 0.01$. The accuracy threshold $\theta$ has been varied within the range of 0.001 to 0.25. The mission duration was set to 150000 s, almost 2 days, which is consistent with AUV battery capacities. Table 1 provides a summary of the parameters used in our case study.

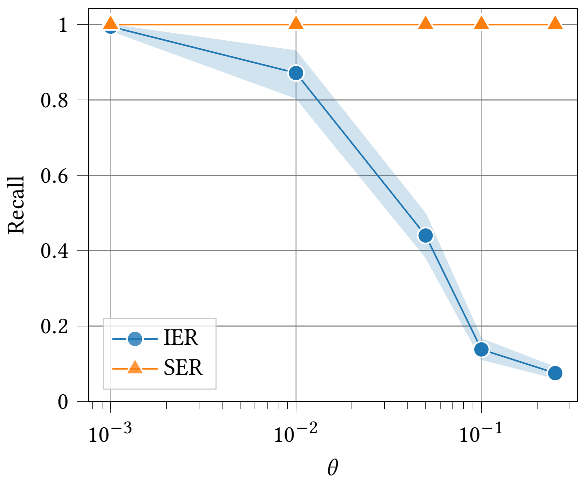


**Figure 6: Recall: number of true anomalies identified divided by the total number of true anomalies (including false negatives).**

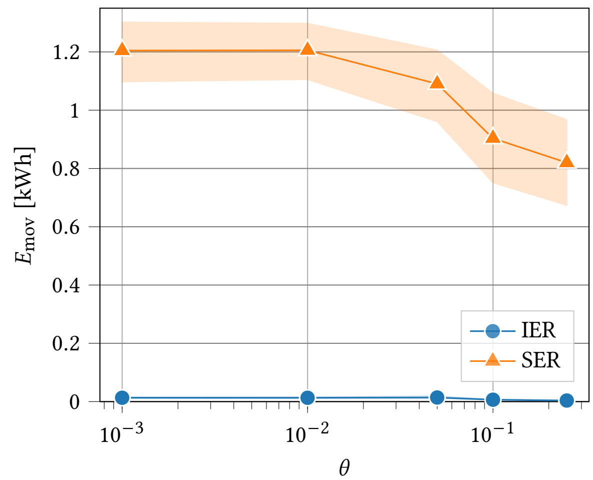


**Figure 7: ASV energy consumption due to movement.**

## 5.1 Precision and Recall

Fig. 5 and Fig. 6 depict the precision and recall performance of the two uncertainty resolution methods. Precision measures the portion of true anomalies correctly identified and resolved by the ASV out of the total number of instances recognized as anomalies, while recall determines the fraction of real anomalies correctly identified as such. We can note that the more conservative behavior of SER results in a far larger number of false alarms: while IER can keep the number of false alarms below 20% in most circumstances, SER has 5 to 10 false alarms for every real detected anomaly, due to its extremely conservative policy of identifying potential anomalies as real ones. On the other hand, SER manages to catch almost all real anomalies, while a significant fraction of anomalies may go undetected with IER. By varying the accuracy threshold, we can change the sensitivity of the two methods to uncertainty: SER will tend to mark fewer doubtful cases as anomalies if $\theta$ is larger, while IER will request more packets before committing to an action. If we increase $\theta$ significantly, most decisions will be based on a small number of packets, leading to generally higher communication performance and fewer collisions. The optimal performance in terms of precision and recall can be obtained by using IER with a low value of $\theta$, which leads the ASV to request multiple packets before making a decision, reducing both false alarms and undetected anomalies at the cost of more transmissions.

## 5.2 Energy Consumption

The distance covered by the ASV and the number of times that the ROV is lowered, have a crucial impact on the total energy consumption. In fact, the energy expended during these movements can be considerable, highlighting the importance of reducing false alarms to conserve energy resources. The total energy consumption is the sum of the energy expended by the ASV and the ROV to move, $E_{mov}$, and the additional energy spent by the AUVs to transmit, $E_{tx}$. To model energy consumption of the AUV, the approach described in [22] was utilized, along with data from [16], which references the Lutra Prop boat. The energy consumption calculation assumes a linear trajectory approximation, without accounting for rotation, acceleration, or deceleration. To model the energy consumption of the ROV, the average consumption of a BLUEROV2, as computed in [23], was employed. As the speed of the ASV is limited, the drag force can be safely neglected [22]. A faster ASV may be able to reach the AUV in a shorter time, but it would also consume significantly more energy due to the non-linear relationship between velocity and energy in high-velocity cases.

Fig. 7 demonstrates the significant energy consumption reduction of the IER method compared to the SER method. These energy savings can be attributed to the more efficient error resolution process of the IER method, which reduces unnecessary movements and false alarms, ultimately leading to lower energy consumption by the ASV. Conversely, Fig. 8 highlights the correlation between the threshold $\theta$, which affects the number of transmitted packets, and the corresponding energy consumption. A larger value of $\theta$, which leads IER to send fewer packets before resolving an uncertain situation, may save some energy, but the effect on the total energy consumption is negligible, as $E_{tx}$ is smaller than $E_{mov}$ by orders of magnitude. The IER method then maintains a much lower total energy consumption when compared to the SER method.

## 5.3 AUV performance

From the AUV's perspective, Fig. 9 shows the improvement achieved by the IER method in terms of the number of true inspected anomalies. Over a simulation run, each AUV solves more anomalies than with SER, as there is no waste of time to go after false alarms. Interestingly, the maximum number of solved anomalies is achieved for a value of $\theta$ that leads to a relatively low recall (around 60%): depending on the severity of undetected anomalies, it might be more prudent to set a lower value of $\theta$ and accept a lower efficiency to increase the system's reliability and safety.

On the other hand, we can see an interesting trend when we consider the total covered distance for each AUV: as Fig. 10 shows, the distance increases with $\theta$ when using both methods. This is

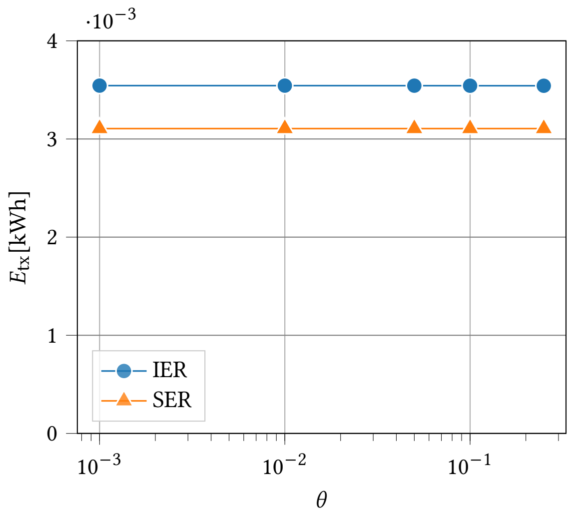


**Figure 8: ASV energy consumption due to transmission.**

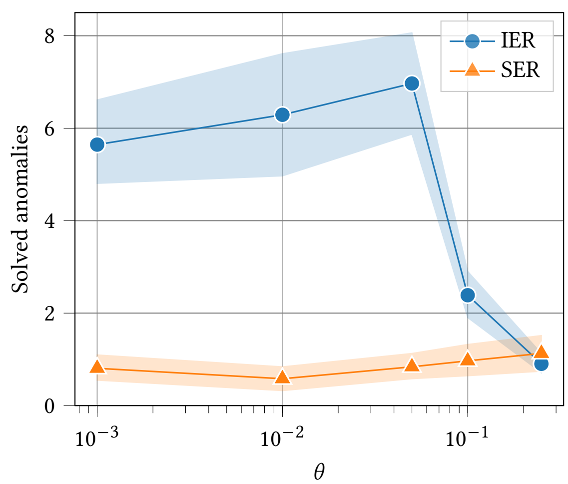


**Figure 9: True anomalies inspected by an AUV during a mission.**

due to the fact that the SER and IER methods become less strict when using a lower value of $\theta$, classifying more samples as normal, leading to lower waiting times and fewer inspections.

## 6 CONCLUSION

The results obtained demonstrate the superior performance of the IER method compared to the simpler SER approach. The IER method not only achieves higher precision and recall in error resolution, but also contributes to significant energy savings for the ASV. Additionally, it enhances AUV productivity by reducing downtime and increasing the total inspected distance. However, further investigation is required to assess the overall quality of performance for the IER method in wider areas and with different error models. Its potential benefits in terms of accuracy, energy efficiency, and productivity make it a valuable area of research and development for underwater inspection systems.

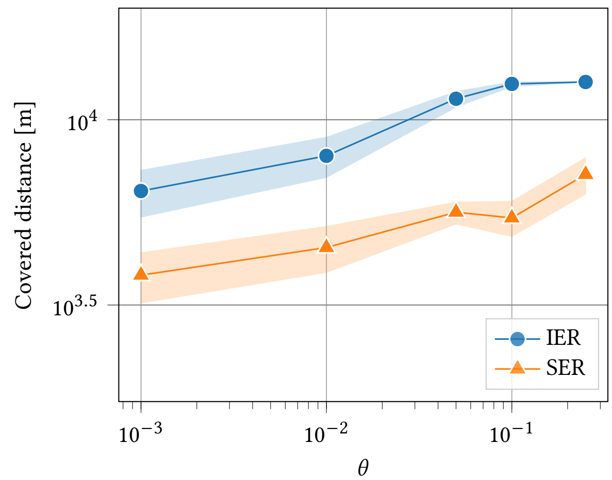


**Figure 10: Distance inspected by a single AUV during the whole mission duration.**

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