

A Survey of Intelligent Underwater Perception and Navigation Systems with Focus on Low-Cost Sensor-Based Mine Detection

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Abstract - Underwater mine detection is a challenging problem in marine robotics due to poor visibility, acoustic noise interference with sensing and non-availability of GPS underwater. Recent research has focused on improving underwater navigation and object detection by combining different types of sensors. Inertial and acoustic sensors are commonly used for navigation, while cameras and sonars are used for perception and detection. Recent studies have also explored the possible use of deep learning methods for identifying mines in sonar images. This survey work focuses on four critical areas: underwater navigation and localization, underwater sensing and perception, sonar-based mine detection using both traditional and deep learning methods, and optical imaging as an additional sensing method. From the literature reviewed, it is observed that there is a need for low-cost system having the aforesaid capabilities. Deep learning methods, particularly Convolutional Neural Networks, have shown promising results for classifying objects in sonar images and reducing false detections. At the same time, the inertial, acoustic, and Doppler-based sensing methods help to maintain position estimates in environments with no GPS availability. Hence there is an opportunity to develop an affordable underwater sensing system. This work therefore explores a low-cost, tethered ROV that combines ultrasonic sensing, metallic-object detection, and offline-trained classification within a limited budget in underwater perception and navigation systems

Key Words: Underwater mine detection, AUV navigation, underwater localization, sensor fusion, sonar imaging, deep learning, underwater perception, synthetic aperture sonar, underwater optical imaging, low-cost robotics

1. INTRODUCTION

Autonomous underwater robotics is an promising area of research with applications in defence, offshore infrastructure inspection, environmental monitoring, and maritime safety. Underwater mine detection is one of the important applications because undetected mines pose a serious risk to vessels, divers, and naval personnel. Traditional mine countermeasure operations have used sonar-equipped vessels and trained divers, but these methods can be time-consuming, expensive, and hazardous. Recent developments in autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) have provided new approaches to underwater detection and

inspection. These platforms can use acoustic sensors, cameras, sonar, and other sensing systems to detect objects and understand their surroundings. Navigation is also a major challenge because GPS cannot be used directly underwater. As a result, underwater vehicles commonly rely on inertial sensors, Doppler velocity logs, acoustic positioning, and combinations of these methods to estimate their position. The literature on AUV navigation also shows that sensor fusion is useful because individual sensors have limitations under different underwater conditions.

AI-based methods have further expanded the capabilities of underwater robots. Machine learning and deep learning techniques are being investigated for tasks such as object detection, classification, path planning, and autonomous control. In mine detection, the existing approaches typically used the processing of sonar images. The more recent research works have investigated the use of neural networks for detecting mine-like objects. Reed et al. presented a model-based approach using statistical segmentation and Dempster-Shafer theory [15], while Le et al. proposed a Deep Gabor Neural Network for mine-like object detection in sonar imagery [16].

However, combining these capabilities into a low-cost system remains a practical challenge. The literature covers underwater navigation, sensing, sonar-based detection, and image processing in considerable detail. Many of the systems use specialised sensors or platforms that may not be easily accessible or affordable for student projects or small research initiatives. Navigation requires relatively expensive sensors or acoustic infrastructure, while underwater perception is affected by factors such as turbidity, scattering, noise, and limited visibility. Based on these observations, this survey examines four areas related to low-cost underwater mine detection: underwater navigation and localization, underwater perception and sensing, sonar-based mine detection, and underwater optical imaging.

The following section reviews the relevant literature and compares the approaches used in these areas. The next section discusses the research gaps identified from the literature and considers a possible approach for developing a low-cost mine-detection and navigation platform.

2. RELATED WORKS

This section reviews the literature relevant to a low-cost underwater mine-detection and navigation system across four themes: navigation and localization for AUVs, underwater perception and sensing, sonar-based mine detection from classical methods through deep learning, and underwater optical imaging as a complementary sensing modality.

2.1 Underwater Navigation and Localization Techniques

Since GPS signals cannot reach through seawater, a large share of AUV research focuses squarely on how a vehicle can figure out where it is. Commercial navigation systems built for this specific purpose typically combine inertial sensors, Doppler logs, and acoustic aiding to hold a position estimate together over a mission [3], and that same blend shows up throughout the academic literature. An early and still widely cited review lays out the main options: inertial navigation, acoustic transponders and beacons, and geophysical navigation, while flagging that reliable inertial sensors and installed acoustic infrastructure both tend to be expensive [8].

A later review categorizes these approaches into three broad families, dead reckoning, signal-based navigation, and map-matching, and adds cooperative navigation as a fourth option where multiple vehicles share position information [9]. Both reviews converge on the same underlying point: no single navigation sensor is accurate or robust enough on its own, which is why sensor fusion keeps coming up as the practical answer.

A survey focused on localization and mapping specifically pushes this further by treating sensor choice as a straightforward trade-off between accuracy, cost, size, and how well a sensor tolerates real underwater conditions, a framing that lines up closely with the low-cost focus of this survey [10]. Another review of passive and active localization techniques makes a similar point from a different angle, comparing how well various sensing approaches hold up depending on the specific underwater environment a vehicle is operating in [11]. A broader positioning and navigation survey adds acoustic localization, underwater vision, and SLAM to the mix alongside GPS buoys and multisensor fusion, and argues that combining several relatively inexpensive sensors, an IMU, a pressure sensor, a compass, acoustic or visual measurements, can outperform any one of them individually [12].

The most recent of these reviews confirms that this is not just an academic preference: it notes a real, ongoing shift in the field toward lower-cost sensors for missions that do not need the accuracy, or the price tag, of a full naval-grade navigation suite [13]. Artificial intelligence is increasingly folded into this picture as well; a review of AI techniques for

underwater navigation and control reports that learning-based methods can noticeably improve localisation and obstacle avoidance over classical control algorithms, particularly in poor visibility, which suggests that low-cost sensor fusion and AI-assisted estimation are complementary approaches rather than competing ones [2].

2.2 Underwater Perception and Sensing Modalities

Navigation is only half the picture; a vehicle also has to make sense of what is actually in front of it. A broad review of intelligent underwater perception surveys how AUVs and ROVs combine acoustic sensors, cameras, sonar, and onboard AI to handle inspection, object detection, and mine-detection tasks, while being upfront about the practical constraints: unreliable communication, poor visibility, noisy sensor readings, and limited onboard power all cap how much processing a vehicle can realistically do in the real world [1].

A more sensor-focused review goes deeper into why this is hard, walking through how light attenuation, refraction, backscattering, and turbidity work against optical sensing underwater, and why acoustic sensors end up carrying more of the load for long-range detection [14]. This review is particularly useful since it does not treat perception in isolation but attempts at tying it directly back to localization, mapping, and trajectory planning.

Operational platforms bear this out in practice: AUVs developed at the Woods Hole Oceanographic Institution pair sonar, cameras, and environmental sensors with navigation systems to carry out autonomous seabed mapping and inspection with minimal human involvement, a working example of perception and navigation being treated as genuinely inseparable rather than as two modules bolted together [4].

2.3 Sonar-Based Mine Detection: From Classical Methods to Deep Learning

Mine detection research has its own, more specific line of development, and it is worth tracing chronologically. An early model-based approach [15] used a Markov Random Field to pick out candidate targets in side-scan sonar images, followed by statistical segmentation to extract highlight and shadow regions and Dempster-Shafer theory to classify them. It represents the generation of automated detection methods that came before deep learning took over, and still serves as a useful baseline against which newer methods get measured. Around the same period, a practical AUV system built specifically for mine reconnaissance [17] showed that these ideas could work outside a lab: the vehicle surveyed real areas using nothing more than side-scan sonar and a multibeam echo sounder, tested against actual dummy mine objects, about as minimal a sensor configuration as this kind of mission gets.

More recent, broader treatments of the same problem [5], [6], [7] describe integrated systems that pair sonar imaging with cameras and navigation modules so a vehicle can flag mine-like objects and plan a route around them at the same time, echoing the same conclusion as the earlier reconnaissance work: detection alone is not the end goal, it needs to feed directly into navigation decisions.

More recent work shifts decisively toward deep learning. A Deep Gabor Neural Network [16] builds parameterized Gabor layers into a feature-pyramid architecture to pull out mine-like features at different scales and orientations, and reports competitive accuracy on a real annotated sonar dataset while keeping the parameter count relatively small, a detail that matters if the goal is eventually running something like this on modest hardware. A related study [18] pairs CNN-based feature extraction with an Extreme Learning Machine to segment side-scan sonar images, and also explores synthesizing sonar imagery to work around a problem that comes up constantly in this field: there simply is not much real, labelled underwater mine data to train on. Higher up the sensing chain, work on synthetic aperture sonar for AUVs [19] tackles image resolution directly, developing signal-processing techniques that reduce multipath interference and, notably, fold the vehicle's own navigation trajectory into the image-forming process itself, tying detection quality back to navigation accuracy in a very concrete way.

2.4 Underwater Optical Imaging as a Complementary Modality

Table -1: Comparative Study

Category	Core Technologies	Strengths	Limitations
AUV Navigation & Localization	INS, acoustic transponders/beacons, dead reckoning, SLAM, multisensor fusion	Enables position estimation without GPS; combines strengths of several inexpensive sensors	Individual sensors drift or lack accuracy; strong trade-off between cost, size, and accuracy
Underwater Perception & Sensing	Sonar, cameras, acoustic sensors	Sonar remains effective in turbid or low-visibility water; links directly to mapping and trajectory planning	Optical sensors limited by light attenuation and backscattering; acoustic sensors can be costly
Classical Sonar-Based Mine Detection	Side-scan sonar, Markov Random Field, Dempster-Shafer classification	Established, interpretable baseline; validated in real AUV reconnaissance missions	Lower accuracy and higher false-alarm rate compared to modern deep learning methods
Deep-Learning Sonar Mine Detection	CNN, Deep Gabor Neural Network, Extreme Learning Machine	High detection accuracy; some architectures remain computationally efficient	Needs annotated sonar datasets, which are scarce; synthetic data still an active workaround
High-Resolution & Synthetic Aperture Sonar	Synthetic aperture sonar, multipath signal processing	Higher image resolution; better separation of objects from seabed clutter	Requires accurate navigation trajectory; processing is computationally demanding
Underwater Optical Imaging	Cameras, image enhancement and restoration algorithms	Cheap, complementary short-range sensing	Heavily affected by turbidity, scattering, and poor lighting

Not all underwater sensing problems are best solved acoustically. A review of underwater image processing [20] surveys the techniques used to fix what water does to a photograph: enhancement, noise reduction, defogging, color correction, and restoration, all aimed at compensating for turbidity, scattering, absorption, and uneven lighting. Sonar remains the more dependable choice for long-range or low-visibility detection, but this review is a useful reminder that cameras still have a role to play as a complementary, and considerably cheaper, sensing option at close range. For a low-cost platform working within a tight budget, that combination, acoustic sensing for range and reliability, optical sensing for cheap close-up confirmation, is worth taking seriously rather than treating sonar as the only real option.

The surveyed papers sketch out a fairly complete picture of what goes into an underwater mine-detection system: reliable navigation without GPS, sensing that works despite poor visibility, and detection algorithms that have moved from statistical models to deep learning over roughly two decades. Cost, however, is treated mostly as a side note. A handful of the navigation reviews [10], [12], [13] raise it directly, and the broader perception and platform papers [1], [4] describe capable systems without dwelling on what they cost to build or replicate, but almost none of the detection-focused papers really grapple with what a genuinely low-cost, resource-constrained version of this kind of system would look like. That is the gap the next section addresses.

3. RESEARCH GAPS AND METHODOLOGICAL APPROACH

The literature reviewed in the previous section identifies several limitations that are relevant to the development of a low-cost underwater system. AUV navigation research has shown the significance of combining multiple sensors because individual sensors have limitations [9], [12]. However, many of the commonly used approaches rely on sensors such as high-accuracy inertial systems, Doppler Velocity Logs (DVLs), or acoustic positioning infrastructure, which can increase the cost and complexity of an underwater platform. The navigation literature also identifies cost as an important factor when selecting sensors for AUV applications [10], [13].

A similar limitation can be observed in underwater mine detection. Recent deep-learning methods have achieved promising results in the detection and classification of mine-like objects in sonar imagery [16], [18].

However, these approaches generally depend on sonar data and labelled datasets that may not be readily available for a small-scale or student-built system. Earlier approaches also relied on specialised sonar systems for detecting and classifying underwater objects [15], [17]. Therefore, there is a need to investigate whether some of these functions can be

implemented using simpler and more affordable sensing hardware.

Based on these observations, the proposed project investigates a low-cost approach to underwater mine detection and navigation. Instead of using the inertial and acoustic navigation systems discussed in Section 2.1, the proposed system uses an IMU-based dead-reckoning approach with offline processing and calibration in MATLAB. For object detection, ultrasonic sensing is used for distance measurement and a custom metal-detector coil is used to identify metal objects that may represent mine-like targets. A lightweight classifier trained using MATLAB is intended to run on an ESP32 rather than relying on the computational resources normally associated with larger sonar-based systems.

The proposed approach does not aim to achieve the same detection accuracy or navigation performance as specialised AUV systems. Instead, the objective is to investigate the feasibility of combining basic sensing, navigation, and classification techniques into a low-cost underwater platform. The resulting system can provide a practical basis for studying the challenges involved in underwater perception and navigation while remaining suitable for academic-scale development and testing.

4. CONCLUSIONS

This survey reviewed research related to underwater navigation and localization, underwater perception and sensing, sonar-based mine detection, and underwater optical imaging. The literature shows that each of these areas has developed significantly. Navigation research has investigated sensor fusion to address the limitations of individual sensors in GPS-denied underwater environments [8]–[13].

Mine-detection research has progressed from model-based sonar-image processing [15] to machine-learning and deep-learning approaches [16], [18]. Other studies have also demonstrated the use of AUVs and multiple sensing technologies for autonomous underwater operations [17], [19].

Despite these developments, the cost and complexity of the sensors and platforms used in many existing systems can make them difficult to reproduce in small-scale research projects. This provides an opportunity to investigate simpler alternatives that combine basic sensing and processing techniques within a limited budget.

The proposed survey work addresses this area through a low-cost, tethered underwater platform using ultrasonic sensing, metal detection, IMU-based navigation, and lightweight classification. The system is intended as a practical investigation of how these functions can be combined rather than as a replacement for specialised naval

or research-grade underwater systems. Future development can focus on improving the integration between perception and navigation, evaluating the system under different underwater conditions, improving object classification, and increasing the level of autonomous operation.

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