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A Review of Learning-Based Sonar Signal Processing Using Neural Networks

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Abstract - Sonar systems are widely used for underwater sensing applications such as navigation, target detection, and environmental monitoring. However, conventional sonar signal processing techniques often rely on handcrafted features and model-based assumptions, which can limit performance in complex and noisy underwater environments. In recent years, learning-based approaches, particularly those using neural networks, have gained increasing attention as a data-driven alternative for sonar signal processing. These methods enable automatic feature extraction and improved adaptability across different operating conditions. This paper presents a review of learning-based sonar signal processing techniques, with emphasis on neural network models applied to single-receiver and multi-receiver sonar systems. Existing studies are categorized into feature-based deep learning approaches, end-to-end learning methods operating on raw or minimally processed acoustic data, and learning-based techniques for hydrophone array processing. The review also discusses general applications of deep learning in underwater acoustic sensing, including sonar imaging and target classification. Key advantages, limitations, and trends within each category are analyzed to provide a structured understanding of the current research landscape. Furthermore, this review highlights common challenges such as data scarcity, computational constraints, and limited generalization across environments. By organizing prior work and identifying research gaps, this paper aims to support the development of robust, data-driven sonar systems and to guide future research in learning-based underwater acoustic signal processing.

Index Terms - Sonar signal processing, underwater acoustics, deep learning, neural networks, end-to-end learning, hydrophone arrays, multi-receiver sonar, machine learning

1. Introduction

Sonar systems play a critical role in underwater sensing and exploration, where electromagnetic waves are highly attenuated and conventional vision-based sensing becomes ineffective.[1], [2] As a result, sonar is widely used in applications such as underwater navigation, object detection, seabed mapping, marine surveillance, and biological monitoring.[3], [4], [5] Both active and passive sonar systems are employed depending on the task, with active sonar transmitting acoustic pulses and analyzing echoes, while passive sonar relies on listening to naturally occurring or man-made acoustic signals.[6] However, underwater acoustic environments are highly complex due to factors such as multipath propagation, ambient noise, signal attenuation, and variability in environmental conditions.[7], [8] These challenges make reliable sonar signal processing a difficult task.

Traditional sonar signal processing methods are largely based on model-driven and rule-based techniques, including beamforming, matched filtering, time-difference-of-arrival estimation, and threshold-based detection.[9], [10] While these methods are well understood and computationally efficient, their performance often depends on carefully selected parameters and strong assumptions about the propagation environment. In practice, such assumptions may not hold due to changing water conditions, interference, and sensor imperfections.[11], [12] Furthermore, classical approaches typically rely on handcrafted features extracted from sonar signals, requiring significant domain expertise and limiting adaptability to new scenarios.[13], [14]

In recent years, machine learning and in particular deep learning have emerged as a promising alternative for sonar signal processing. Neural networks can automatically learn discriminative representations from data, reducing the need for manual feature engineering.[15], [16], [17] Learning-based methods have demonstrated improved performance in tasks such as target detection, classification, localization, and direction-of-arrival estimation when compared to conventional techniques.[18], [19] Convolutional neural networks have been especially popular due to their ability to process time frequency representations and capture local signal patterns. These advantages have motivated increasing interest in applying neural networks to both active and passive sonar systems.[20]

A growing body of research has also explored end-to-end learning approaches, where neural networks operate directly on raw or minimally processed acoustic signals. By learning directly from waveform-level data, such models aim to preserve information that may be lost during preprocessing and allow the network to jointly optimize feature extraction and task-specific decision making.[21] At the same time, the use of multiple receivers or hydrophone arrays has gained attention, as spatial diversity provides valuable information for improving robustness and accuracy. Learning-based methods applied to multi-receiver sonar systems offer new opportunities to jointly model spatial and temporal characteristics of underwater acoustic signals.[22]

This review focuses on learning-based sonar systems that use one or multiple receivers and neural networks, with particular emphasis on approaches that process raw or minimally processed acoustic data. The paper surveys exist in feature-based deep learning, end-to-end learning, and multi-receiver sonar processing, highlighting key methodologies and application domains. By organizing prior studies into clear categories, this review aims to provide a structured overview of current trends, identify limitations in existing approaches, and outline open research challenges. The insights presented in this review are intended to support future research on robust, data-driven sonar systems capable of operating in complex underwater environments.

2. Overview of Sonar Signal Acquisition

Sonar signal acquisition is the process by which underwater acoustic information is transmitted, received, and converted into digital signals for further processing. Due to the high attenuation of electromagnetic waves in water, sonar remains the primary sensing modality for underwater environments. Sonar systems are generally categorized as active or passive depending on whether an acoustic signal is transmitted into the environment.

In active sonar systems, an acoustic transmitter emits a known sound pulse into the water. When this pulse encounters an object or boundary, part of the energy is reflected back and captured by one or more receivers. The echoes received contain information related to the target's range, material properties, and spatial location. Active sonar is commonly used in applications such as obstacle detection, seabed mapping, and target classification. However, the echo signals are often corrupted by noise, reverberation, and multipath propagation, making reliable signal interpretation challenging.[23], [24]

Passive sonar systems do not transmit acoustic energy. Instead, they rely on receiving sounds generated by external sources such as vessels, marine animals, or environmental processes. Passive sonar is widely used in surveillance and monitoring applications, where stealth and long-term observation are required.[25], [26] The received signals in passive systems are typically continuous and highly variable, with overlapping sources and strong background noise. As a result, extracting meaningful information from passive sonar data requires robust processing techniques.

The receiver configuration plays a significant role in sonar signal acquisition. A single hydrophone captures a one-dimensional time-domain signal, which may be sufficient for basic detection or classification tasks.[27] However, single-receiver systems lack spatial information and are sensitive to noise and environmental changes. To address these limitations, many sonar systems employ multiple receivers arranged in hydrophone arrays.[28] By capturing signals at different spatial locations, arrays provide phase and amplitude differences that can be exploited for beamforming, source localization, and direction-of-arrival estimation. This spatial diversity improves robustness and enables more advanced sensing capabilities.[29], [30]

Once acoustic signals are received, they are typically digitized and either processed directly or transformed into alternative representations. Conventional sonar processing often involves preprocessing steps such as filtering, beamforming, and time frequency analysis. Representations such as spectrograms, cepstrograms, or covariance matrices are commonly used as inputs to learning-based models.[31], [32] These processed representations emphasize specific signal characteristics and reduce noise, but they may also discard potentially useful information.

More recently, end-to-end learning approaches have emerged that operate on raw or minimally processed acoustic data. In these systems, neural networks are trained to learn both feature extraction and task-specific decision making directly from waveform-level inputs.[33], [34] This approach reduces dependence on expert-designed preprocessing and allows models to adapt more flexibly to different operating conditions. However, raw-data learning typically requires larger datasets and careful network design, especially in multi-receiver configurations.

Understanding the sonar signal acquisition process including transmitter behavior, receiver configurations, and data representations is essential for interpreting learning-based sonar research. It also provides the foundation for comparing feature-based and end-to-end approaches, as well as single-receiver and multi-receiver systems, which are discussed in the following sections.[35], [36]

3. Feature-Based Deep Learning for Sonar Signal Analysis

Several studies have explored the use of feature-based deep learning techniques for sonar signal analysis, where acoustic signals are first transformed using signal processing methods before being classified by neural networks. These approaches rely on engineered representations such as time–frequency transforms, sparse features, or beamformed spectrograms to extract discriminative information from sonar data.

A notable example is the work[37], titled Automatic Object Classification for Low-Frequency Active Sonar using Convolutional Neural Networks. In this study, active sonar echoes are transformed into the time frequency domain and provided as input to a convolutional neural network for object classification. The CNN is trained using data collected during two sea trials and validated on a third trial conducted in different environmental conditions. The results demonstrate that the CNN-based classifier significantly reduces false alarm rates and outperforms a previously developed traditional feature-based classifier.

Feature sparsification has also been investigated to improve classification efficiency and robustness. In Classification of sonar echo signals in their reduced sparse forms using complex-valued wavelet neural network[38] propose transforming sonar echoes into sparse representations using complex-valued wavelets. These reduced representations are then classified using a wavelet neural network. Their results indicate that combining sparse feature extraction with neural networks can achieve improved classification performance while reducing input dimensionality.

Beyond classification, feature-based deep learning has been applied to acoustic localization tasks. In Convolutional neural network for single-sensor acoustic localization of a transiting broadband source in very shallow water[39] employ cepstrum-based features extracted from spectrograms to train a CNN for passive source localization. The study shows that CNN-based localization outperforms traditional model-based approaches, particularly under shallow-water conditions with strong multipath effects.

Comparative analyses between neural networks and conventional classifiers further highlight the advantages of learning-based approaches. In Comparing neural networks with conventional classifiers for fin whale vocalizations in beamformed spectrograms of coherent hydrophone array[40] evaluate neural networks against logistic regression, support vector machines, and decision trees. Using beamformed spectrograms and extracted acoustic features, the neural network classifier achieves higher accuracy, precision, and recall in identifying fin whale vocalizations from large-scale passive acoustic datasets.

Overall, these studies demonstrate that feature-based deep learning methods particularly CNNs operating on time–frequency or sparsified representations—are effective for sonar signal classification and localization. However, these approaches still rely on carefully designed preprocessing and feature extraction steps, which motivates more recent research into end-to-end learning methods that operate directly on raw sonar signals.

4. End-to-End Learning from Raw or Minimally Processed Sonar Signals

Recent research has increasingly explored end-to-end deep learning approaches for sonar and underwater acoustic signal processing, aiming to reduce reliance on handcrafted feature extraction. Unlike feature-based methods, these approaches train neural networks directly on raw or minimally processed acoustic data, allowing the models to automatically learn discriminative representations from the signal itself.

One example of waveform-level end-to-end learning is presented in "Deep-learning based ocean bottom seismic waveform classification"[41]. In this work, convolutional neural networks are trained directly on seismic waveforms to perform classification tasks without explicit feature engineering. Although the study focuses on seismic data, the methodology closely aligns with sonar signal processing, as both domains involve acoustic wave propagation in complex environments. The results demonstrate that deep networks can successfully learn meaningful representations directly from waveform data, supporting the feasibility of end-to-end acoustic signal learning.

A more sonar-specific application of raw-signal learning is described in "Design of Deep Learning Acoustic Sonar Receiver Using Raw Acoustic Signals"[42]. This study explicitly proposes a receiver-side deep learning architecture that operates directly on raw acoustic signals captured by sonar sensors. By replacing parts of the conventional sonar processing chain with a neural network, the proposed approach demonstrates that end-to-end learning can be effectively applied at the receiver level, offering a compact and data-driven alternative to traditional signal processing pipelines.

End-to-end learning has also been explored for target recognition tasks in sonar systems. In “A Deep Learning Approach to Target Recognition in Side-Scan Sonar Imagery”, deep convolutional neural networks are trained directly on side-scan sonar measurements to identify and recognize underwater targets. The approach avoids manual feature extraction by allowing the network to learn relevant spatial and intensity-based patterns directly from sonar data, demonstrating competitive performance in real-world scenarios[43].

In addition, “Deep Learning based Framework for Underwater Acoustic Signal Recognition and Classification”[44] presents a data-driven framework for underwater acoustic signal classification. While minimal preprocessing is applied to convert signals into suitable representations, feature learning is performed automatically by convolutional neural networks rather than through handcrafted descriptors. The study reports high classification accuracy and highlights the robustness of deep learning models when trained on large acoustic datasets.

Overall, these studies indicate that end-to-end or minimally processed learning approaches can effectively model sonar and underwater acoustic signals without heavy reliance on expert-designed features. However, most existing works focus on single-sensor configurations and task-specific models. This limitation motivates further investigation into multi-receiver and multi-task end-to-end learning frameworks, which may better exploit spatial diversity and shared representations in advanced sonar systems.

5. MULTI-RECEIVER AND HYDROPHONE ARRAY–BASED DEEP LEARNING FOR SONAR PROCESSING

Multi-receiver sonar systems and hydrophone arrays provide spatial diversity that enables improved detection, localization, and classification in underwater acoustic environments. Recent research has increasingly combined neural networks with array signal processing techniques to address limitations of classical beamforming and direction-of-arrival (DOA) estimation, particularly under low signal-to-noise ratio (SNR) and multipath conditions.

An example of learning-based adaptive beamforming is presented in “Adaptive beamforming for uniformly-spaced linear hydrophone array using temporal convolutional neural networks”[45]. In this study, raw multi-channel waveforms acquired from a uniformly spaced linear hydrophone array are directly provided as inputs to temporal convolutional neural networks. The network predicts beamforming filter coefficients in the time domain and is jointly trained with a CNN-based classifier to improve target recognition accuracy. Experimental results obtained from coastal water trials demonstrate improved adaptability to spatially correlated noise compared with conventional delay-and-sum and filter-and-sum beamforming methods.

Deep learning has also been applied to multi-sensor acoustic source localization. In “Multitask convolutional neural network for acoustic localization of a transiting broadband source using a hydrophone array”[46] propose a multitask CNN that jointly estimates the range and bearing of a moving acoustic source. The model operates on cepstrogram-based and cross-correlogram-based feature maps derived from multiple hydrophones. The results show that the multitask CNN outperforms both single-feature CNNs and conventional model-based passive ranging methods, particularly in shallow-water environments with strong multipath propagation.

Neural networks have also been integrated with classical array processing algorithms for DOA estimation. In "DeepMUSIC: Multiple Signal Classification via Deep Learning"[47] introduce a deep learning framework that maps array covariance matrices to spatial spectra traditionally produced by the MUSIC algorithm. By learning this nonlinear mapping using convolutional neural networks, the proposed method achieves accurate multi-source DOA estimation with reduced computational complexity compared to conventional MUSIC-based approaches.

Similarly, "Research on DOA Estimation Method of Vector Hydrophone Array in Low SNR Based on CNN"[48] applies convolutional neural networks to vector hydrophone array data for high-precision DOA estimation. The CNN processes multi-channel inputs formed from the real, imaginary, and phase components of the array covariance matrix and outputs a 360-degree spatial spectrum. Simulation and experimental results show that the proposed method outperforms the traditional MUSIC algorithm, particularly under low-SNR conditions and in the presence of noise and array imperfections.

Overall, these studies demonstrate that deep learning–based processing of multi-receiver and hydrophone array data can significantly enhance beamforming, localization, classification, and DOA estimation performance. By exploiting spatial information and learning data-driven representations from multi-channel acoustic signals, array-based neural network approaches offer improved robustness and adaptability compared with conventional model-based sonar processing techniques.

6. General Underwater Acoustic Deep Learning

General underwater acoustic deep learning research focuses on applying neural networks to higher-level acoustic representations and application-oriented tasks, rather than emphasizing detailed sonar signal chains or array configurations. These studies demonstrate how deep learning can be used to automatically interpret underwater acoustic data in complex environments where conventional rule-based processing is often insufficient.

The study "Classification of anti-submarine warfare sonar targets using a deep neural network" investigates the use of deep learning to reduce false-alarm rates in modern anti-submarine warfare sonar systems operating in littoral environments. A deep neural network is trained on sonar data containing a high number of false detections and is shown to outperform simple signal-to-noise ratio–based thresholding methods, even when the available dataset is relatively small. The authors further demonstrate that data augmentation techniques significantly improve classification performance under limited training data conditions[49].

Deep learning has also been applied to sonar imaging tasks using synthetic aperture sonar (SAS). In "Multi-view SAS image classification using deep learning", a multi-view convolutional neural network framework is proposed to classify SAS images by integrating information from multiple observation perspectives. By learning discriminative features directly from sonar images, the approach achieves improved classification accuracy compared to single-view methods, highlighting the effectiveness of deep learning for image-based underwater sensing applications[50].

Another application of deep learning to sonar imagery is presented in "Signalization of objects on the sonar images using neural network segmentation methods." This study applies convolutional neural network–based segmentation models, including U-Net, SegNet, and DeepLab architectures, to automatically identify objects and structural elements in side-scan sonar images. The results show that neural network–based segmentation can effectively highlight objects of interest and improve the interpretability of sonar images, even in the presence of noise and clutter[51].

Overall, these studies demonstrate that deep learning has been successfully adopted for general underwater acoustic and sonar imaging applications, including target classification and object signalization. While these approaches typically operate on processed representations such as sonar images or higher-level acoustic features, they provide important insights into the broader applicability of deep learning techniques in underwater sensing systems.

7. Identified Gap and Proposed Solution

Despite the successes above, several challenges remain in applying deep learning to sonar:

- Reliance on engineered features: Many state-of-the-art systems still depend on manual preprocessing (e.g. spectrograms, beamforming). Bridging fully end-to-end learning for all sonar tasks is an ongoing challenge.
- Data scarcity and variability: Underwater data are often limited or expensive to collect. Studies note performance drops with small datasets and highlight the need for augmentation. Models also struggle to generalize across different environments (e.g. varying water conditions or sensor setups).
- Single-task/single-sensor models: Most current works address specific tasks (classification, localization) with one sensor or a fixed array. There is a gap in developing multi-task or transfer-learning frameworks that can handle multiple objectives or adapt to new sensors.
- Computational and real-time constraints: Deep models can be computationally demanding. Real-world sonar systems require real-time or low-power processing, so efficient architectures and hardware implementation are needed.
- Robustness to noise and multipath: While DL methods have shown improvements, challenging conditions like low SNR, strong multipath, and nonstationary noise still pose problems. Adversarial conditions may degrade model performance in unexpected ways.

Addressing these gaps will require larger and more diverse sonar datasets, innovative network designs, and tighter integration with classical signal processing knowledge.

8. Conclusion

This review has examined recent advances in learning-based sonar signal processing, with a focus on neural network approaches applied to single-receiver and multi-receiver sonar systems. Sonar remains a fundamental sensing modality in underwater environments, but traditional signal processing techniques often face limitations due to noise, multipath propagation, and reliance on handcrafted features. The studies reviewed in this paper demonstrate that data-driven methods can effectively address many of these challenges by learning robust representations directly from acoustic data.

Feature-based deep learning approaches have shown strong performance by combining conventional signal transformations with neural network classifiers. These methods benefit from domain knowledge and often achieve reliable results in classification and localization tasks. However, their dependence on carefully designed preprocessing steps can limit adaptability across different environments and system configurations. In contrast, end-to-end learning approaches reduce the need for manual feature engineering by operating on raw or minimally processed sonar signals. Such models allow joint optimization of feature extraction and task-specific inference, offering greater flexibility and the potential to capture information that may be lost during preprocessing.

The review also highlighted the growing importance of multi-receiver and hydrophone array–based learning methods. By exploiting spatial diversity, neural networks can enhance beamforming, source localization, and direction-of-arrival estimation, particularly under low signal-to-noise ratio and complex propagation conditions. These approaches demonstrate the advantage of integrating spatial and temporal information within unified learning frameworks. Additionally, general applications of deep learning to underwater acoustic data, including sonar imaging and object identification, further illustrate the broad applicability of neural networks in underwater sensing.

Despite these advances, several challenges remain, including data scarcity, computational constraints, and limited generalization across environments. Many existing studies focus on specific tasks or system setups, indicating a need for more unified and scalable learning frameworks. Future research efforts should aim to develop robust, end-to-end, and multi-receiver learning models that can operate reliably in real-world underwater conditions. Overall, learning-based sonar signal processing represents a promising direction, with significant potential to improve the performance and adaptability of next-generation underwater sensing systems.

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