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The least squares concept in reducing noisy signal of single-beam acoustic systems: Ocean depth measurement to support maritime defense systems

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Abstract

Indonesia's vast ocean territory presents both opportunities and security challenges, requiring robust maritime defense. Effective sea defense includes surface patrols with naval vessels and aircraft, alongside underwater surveillance using submarines and detection systems. Advanced acoustic technology, such as Single Beam Echo Sounder (SBES) sonar, is essential for underwater depth measurement. However, environmental noise often disrupts sonar recordings, necessitating noise reduction techniques. This study applies the Least Mean Square (LMS) filter, an adaptive algorithm that adjusts filter coefficients based on error minimization. Its real-time adaptability enhances noise suppression, improving sonar signal quality. The results indicate that the LMS filter achieves an optimal Signal-to-Noise Ratio (SNR) of 6.7248 dB, surpassing other methods. Furthermore, it accurately identifies signal delays, crucial for precise depth measurement. Enhancing underwater acoustic technology through LMS filtering supports improved hydrographic surveys, benefiting scientific research, commercial navigation, and military operations in securing Indonesia's maritime domain.

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INTRODUCTION

Indonesia is a country that has a wider area of water than land (Hidayah & Singh, 2021). The vast waters can be both a wealth and a threat to Indonesia's maritime security, so there is a need for maritime security through strong maritime defense (Wahidun et al., 2024). Underwater acoustic technology is one way of improving maritime defense by detecting the condition of the sea area which includes the presence of biodiversity, measuring the depth of the sea floor, and detecting objects or foreign objects that can pose a threat to the Unitary State of the Republic of Indonesia (Xie et al., 2022). Underwater acoustic technology faces several challenges in its development because the waters, especially the vast oceans, have underwater noise disturbances or noise from various natural sources, such as the sound of rain, breaking waves, and the sounds of marine life (Mishachandar & Vairamuthu, 2021). In addition to noise from natural sources, noise can also come from man-made devices, such as the sound of ships, military sonar, and others (Brennecke et al., 2023). These noises can interfere with the results of underwater acoustic technology, disrupting recordings and even losing the original data of the signal. Furthermore, the complex noise of the marine environment can cause a decrease in the quality of the acoustic signal itself (Wang et al., 2021).

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Problems caused by noise can be solved with the help of software through signal processing (Martínez et al., 2022). Signal processing is a field of study that studies and develops methods or algorithms related to signal analysis, manipulation, interpretation, and transformation (Sharma & Meena, 2024). Signal processing can be done so that the signal mixed with noise can be reduced. Based on their representation, signals are divided into analog signals and digital signals (Sharma et al., 2020). One form of signal processing that can be done is signal filtering. Signal filtering is a form of signal processing that aims to improve the quality of the resulting signal by using an appropriate filter (Ahmed & Al-Obaidi, 2022). According to the central limit theorem of statistics, noise in underwater acoustic technology can be described as Gaussian noise. However, in reality, underwater acoustic technology contains Gaussian and non-Gaussian noise which causes difficulties in applying the best filter (Jagan & Rao, 2020). One of the difficulties in acoustic technology is caused by obstacles in building a threshold function in noise detection, so a filter is needed that is precise in reducing Gaussian and non-Gaussian noise in actual underwater acoustic signals.

Signals with Gaussian noise and non-Gaussian noise can be overcome by using various types of filters, as in several studies that have been conducted, one of which uses an average filter type. The way the average filter works is by determining the average amplitude in a certain kernel or window so that it can smooth the signal by reducing fluctuations or low-level noise as well as fine details in the signal (Kumar et al., 2021). This filter is usually effective in removing Gaussian noise rather than non-Gaussian noise. In other studies, a median filter is used which is more suitable for non-Gaussian noise because it tends to retain details in the original signal better than the average filter (Zhang et al., 2024). This is due to the way the median filter works in replacing sample values with median values in a certain kernel or window (Guo et al., 2022).

The noise-filled conditions under the sea require filter algorithms on underwater acoustic signals to produce maximum signals in maintaining sea defense and security. Therefore, research is needed on noise reduction in single-beam underwater acoustic signals using a recording device. This study will discuss how to reduce noise in single beam underwater acoustic signals using a recording device and the application of methods using algebraic approaches and numerical methods using the Least Mean Square (LMS) filter. The LMS filter is an adaptive filter that can adjust to changes in input signals which are expected to produce acoustic signals with reduced noise from underwater in supporting marine defense and security through underwater acoustic technology.

In noise reduction, precise depth measurements play a fundamental role in many aspects of maritime defense. The ability to accurately determine ocean depth is important for various military applications, including strategic planning, navigation, and security operations (Rahman et al., 2021). Ocean depth is defined as the vertical distance from the sea surface to the seafloor, which can vary significantly across different regions due to tectonic, sedimentary, and hydrodynamic factors (Arafat et al., 2025; Hibiya, 2022). Knowledge of seafloor topography is vital for identifying potential hazards, establishing secure naval routes, and supporting underwater operations. However, obtaining precise depth measurements can be challenging due to the noise interference, which can distort or obscure the acoustic signals used for measurements (Skålvik et al., 2023). Therefore, it is critical to apply effective noise reduction techniques to ensure the accuracy and reliability of the data.

Reliable depth measurements not only enhance maritime situational awareness but also support broader defense strategies that depend on high-quality oceanographic information. The uses of depth measurements carried out in the field of defense, namely:

1. Ocean Mapping: An echosounder can be used to map ocean depths and seafloor topography (Sørensen et al., 2025). This is important for navigation of military vessels and operations in waters that are not sufficiently exposed. With proper mapping, navies can plan their operations more efficiently and identify places that might be dangerous or useful.
2. Obstacle Detection: Using the data collected by an echosounder, navies can detect obstacles below the water's surface, such as coral reefs or shipwreck debris (Kot, 2022). This is essential for safe navigation, especially in situations where there is a threat of sea mines or other obstacles.
3. Diving and Underwater Operations: Precise ocean depths are essential for diving operations, underwater construction, and maintenance of marine infrastructure such as communication cables or energy installations. Echosounder helps in determining the exact location for such operations (Grządziel, 2021).

4. Investigation and Intelligence: The data collected by an echosounder can also be used for intelligence and investigation purposes (Klein et al., 2024). For example, seafloor mapping can provide strategic information about the topography of a particular region, which can be used in planning military operations.

Counter Vessel Detection: Although single-beam echosounders are not specifically designed for vessel detection, the information obtained from depth measurements can be used as part of a larger vessel detection system. Changes in depth or acoustic reflection patterns may indicate the presence of ships or other objects in the vicinity of a particular area.

METHOD

This study employs a signal processing design aimed at reducing noise in underwater acoustic signal to improve maritime defense capabilities in measuring sea depth. Data acquisition took place at the Indonesian Navy Research and Development Service (Dinas Penelitian dan Pengembangan TNI-AL), while data processing was performed at the Indonesia Defense University using MATLAB R2025a. Acoustic signal data were collected through controlled recordings using a transducer-based audio emission system. The recordings were captured cia earphones and saved as .wav files. These signals were then processed into discrete data within MATLAB. To simulate real marine conditions, artificial noise in the form of Gaussian and impulsive noise was added. Noise reduction was carried out using three filtering methods: moving average, moving median, and Least Mean Square (LMS) methods. The performance of each filtering method was evaluate using the Signal-to-Noise Ratio (SNR) metric to assess their effectiveness in restoring the quality of the original signal.

Proposed Method

The Least Mean Square filter is a filter designed to minimize the difference between the filter output and the reference signal (Shaddeli et al., 2021). This filter is very effective on signals that have dynamic characteristics because of its ability to adapt quickly to changes. The adaptivity of the LMS filter makes it superior to moving average filters and moving median filters, which tend to be less responsive to rapid signal variations. The following is the equation used in the LMS algorithm, which begins by calculating the output prediction y(n) (Took & Mandic, 2022):

$$y(n) = \mathbf{w}^T(n) \, . \, \mathbf{x}(n) \tag{1}$$

where: $\mathbf{w}(n)$: Filter weight vector at time n
$\mathbf{x}(n)$: Input vector at time n

After obtaining the output prediction, the error is calculated as the difference between the reference signal d(n) and the filter output y(n) with the following equation (Silva et al., 2021).

$$e(n) = d(n) - y(n) \tag{2}$$

Next, the filter weight is updated using the LMS update equation with μ the step size as follows (Khan et al., 2021).

$$\mathbf{w}(n+1) = w(n) + \mu . e(n) . x(n) \tag{3}$$

Evaluation Matrices

Signal to Noise Ratio (SNR)

Signal to Noise Ratio is a method used to measure the magnitude of signal to noise in decibels (dB) (Hennig, 2023; Winters et al., 2022). The SNR method compares the level of the filtered signal with the signal that still has noise. The following is the equation used in calculating SNR (Poulinakis et al., 2023).

$$SNR = 10 \log_{10} \frac{\sum_n x^2(n)}{\sum_n e^2(n)} \tag{4}$$

where: $x(n)$: original signal without noise
$e(n)$: noise on the signal

RESULTS AND DISCUSSION

This research utilizes experimental acoustic signal data, originally using a transducer-based system in a controlled environment. The data were at the Indonesian Navy Research and Development Service ((Dinas Penelitian dan Pengembangan TNI-AL)) and processed at the Indonesia Defense University, which obtained from simulated underwater acoustic signals original with a Single Beam Echosounder (SBES). The original or recorded signal is captured in .wav audio format. A reference signal is generated using the traveling wave equation to simulate the ideal response typically found in sonar microcontroller systems. Both signals are imported into MATLAB and converted into vector format for further processing. Figure 1 displays the original signal alongside the constructed reference signal, visually confirming their similarity before noise is introduced.

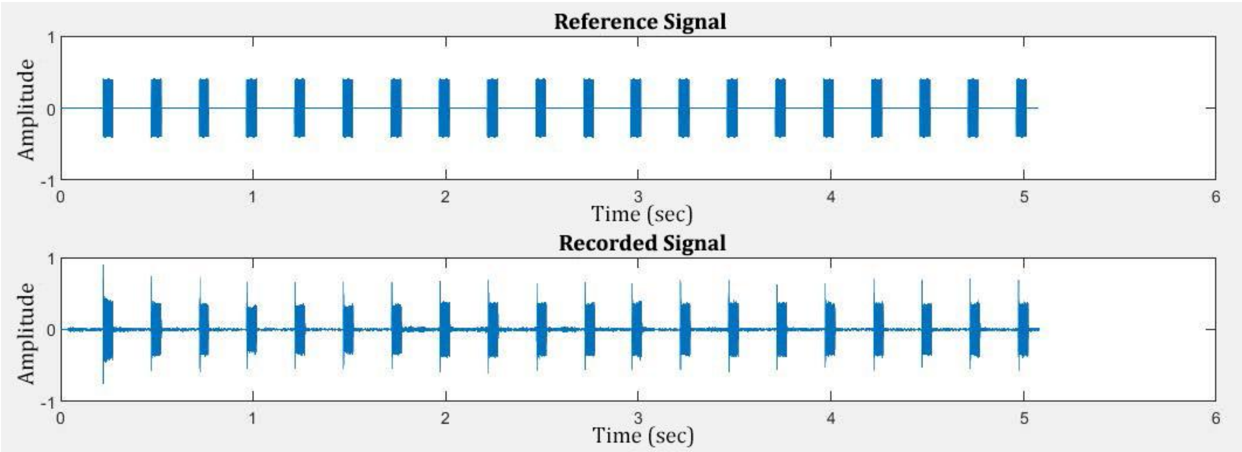

Figure 1. Visualization of the original signal and reference signal

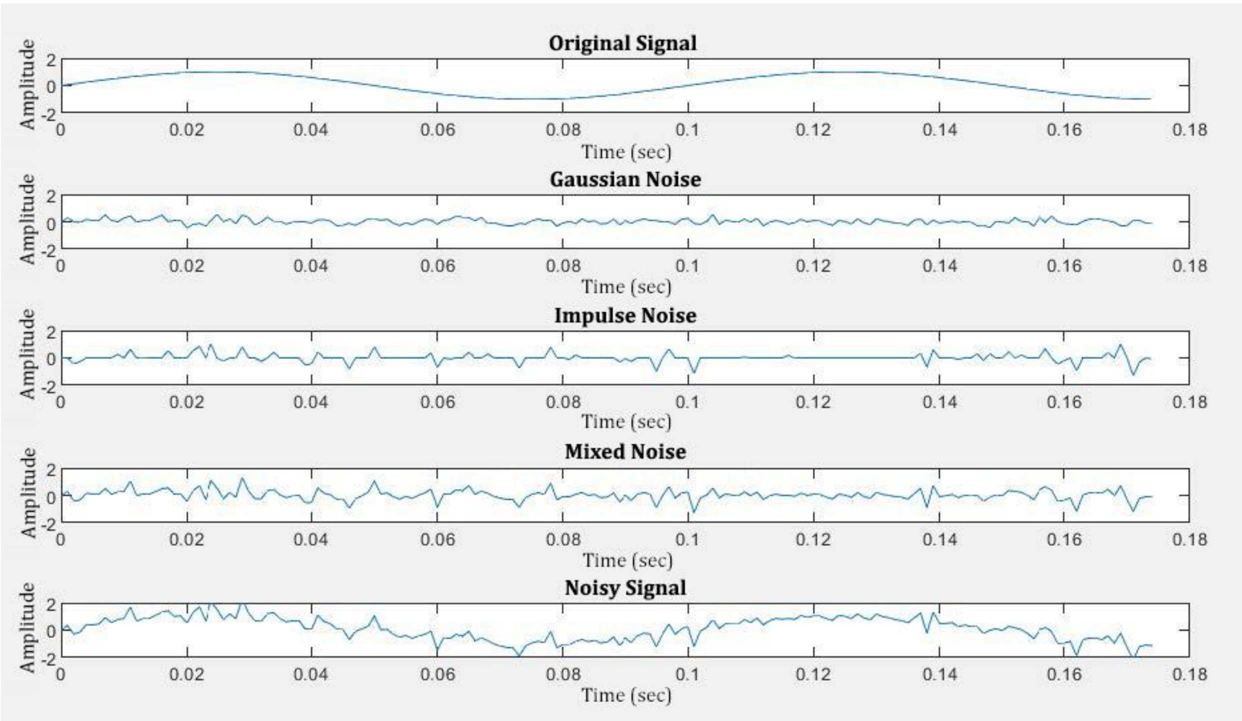

Figure 2. Original sinusoidal signal, noise, and sinusoidal signal added with noise

The original signal is then subjected to additive noise with a summation operator. Noise can come from a variety of sources including electromagnetic interference as well as unwanted ambient signals that can interfere with the original signal. In the context of signal processing, artificial noise can cause interference to the data, reduce the information in the signal, or even generate false information. Artificial noise is therefore used to develop effective techniques to reduce or eliminate such noise, thus enabling more effective signal processing (see Figure 2). To recover the original signal from noise interference, several filtering techniques were tested and compared, which include moving average filter, moving median filter, exponential average filter, and least mean square (LMS) filter. All methods were evaluated using the same experimental noisy signal. The signal mixed with noise is filtered using the least mean square (LMS) method, which is the main method in this research. To assess its effectiveness, both the moving average and moving median filters are used for comparison. These benchmark methods help evaluate how well LMS reduces noise. Figure 3 shows the visual performance of each filter, where LMS demonstrated the most accurate recovery of the original waveform.

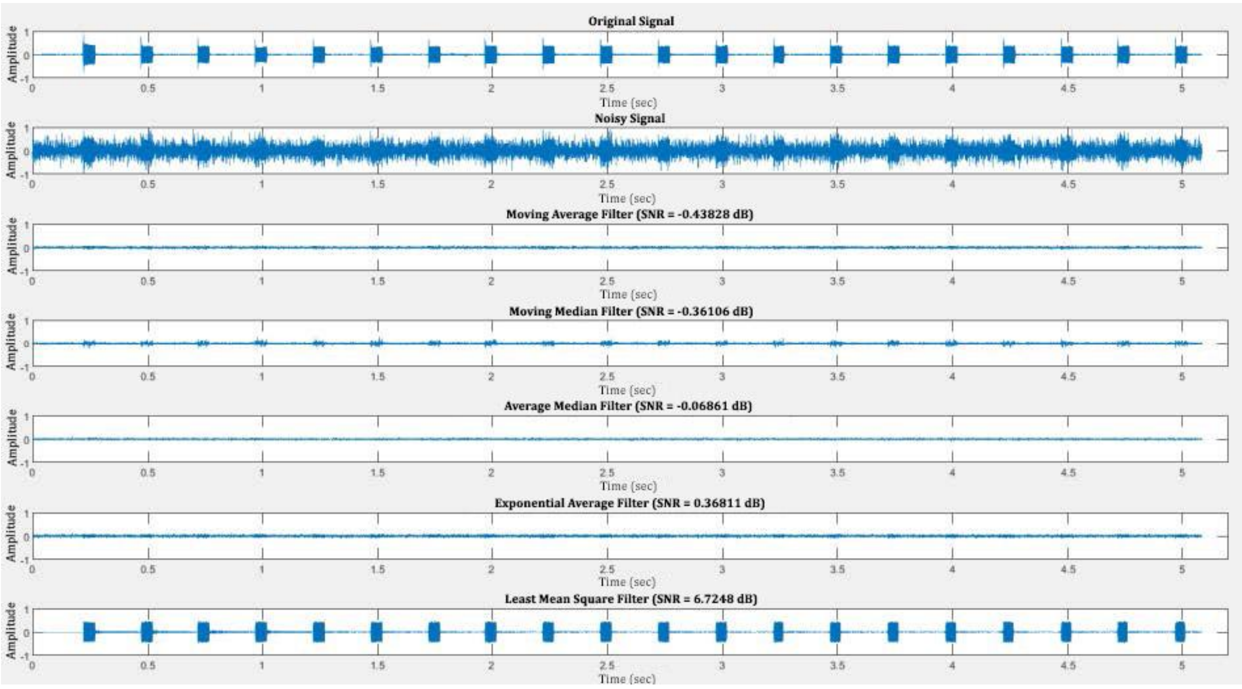

Figure 3. Comparison of the tested filters

The LMS method stands out due to its adaptive nature-it updates its weight based on the error between the estimated and reference signal. Unlike static approaches like moving average or median, which apply the same smoothing rule regardless of input variability, LMS dynamically adjusts based on signal conditions. This adaptability is crucial in processing acoustic signals, which are inherently noisy due to the presence of both Gaussian and non-Gaussian noise. Figure 3 shows a comparison of filter methods, indicating that the moving average, moving median, and even the combination of both yield poor results when used to remove noise in acoustic signals. These methods fail to effectively accommodate the dynamic and complex characteristics of underwater acoustic noise. In contrast, the adaptive filtering algorithm of the LMS method produces results that are the most similar to the original signal.

Table 1. Filter evaluation using SNR

Filter	**SNR (dB)**
Moving average filter	-0.43828
Moving median filter	-0.36106
Average median filter	-0.06861
Exponential average filter	0.36811
Least mean square filter	6.7248

The superiority of the LMS method is further supported by the Signal-to-Noise Ratio (SNR) values presented in Table 1, which quantitatively demonstrates its effectiveness in preserving signal quality amidst noise interference.

The Signal-to-Noise Ratio (SNR) metric further supports the LMS filter's superior performance in denoising acoustic signals. As shown in Table 1, the highest SNR value is achieved by LMS filter, which reaches 6.7248 dB, significantly outperforming static filters such as the moving average and moving median, which yield SNR values below 1 dB. This numerical result confirms the visual observations in Figure 3, where the LMS filter output closely resembles the original signal, whereas the static filters fail to effectively suppress the noise. The inadequacy of static filters in this context is primarily due to the nature of acoustic signals, which are often corrupted by both Gaussian and non-Gaussian noise, rendering fixed smoothing techniques less responsive to signal variability. In contrast, the LMS method stands out due to its adaptive learning capability, which updates filter coefficients based on the estimation error, allowing it to adjust dynamically to fluctuating noise characteristics.

This study takes a Single Beam Echosounder (SBES) type underwater acoustic signal recording using the LMS algorithm which is used to determine the delay on a noise-mixed signal by adapting a filter that produces an output that is closest to the original signal. By analyzing the difference between the received signal and the expected signal, the LMS algorithm iteratively adjusts the filter parameters to minimize the mean square error. Thus, the LMS algorithm can help identify the delay between the noise signal and the reference signal, enabling the recovery of signals that are distorted or delayed due to noise. The results of the research that has been done are shown in Figure 4.

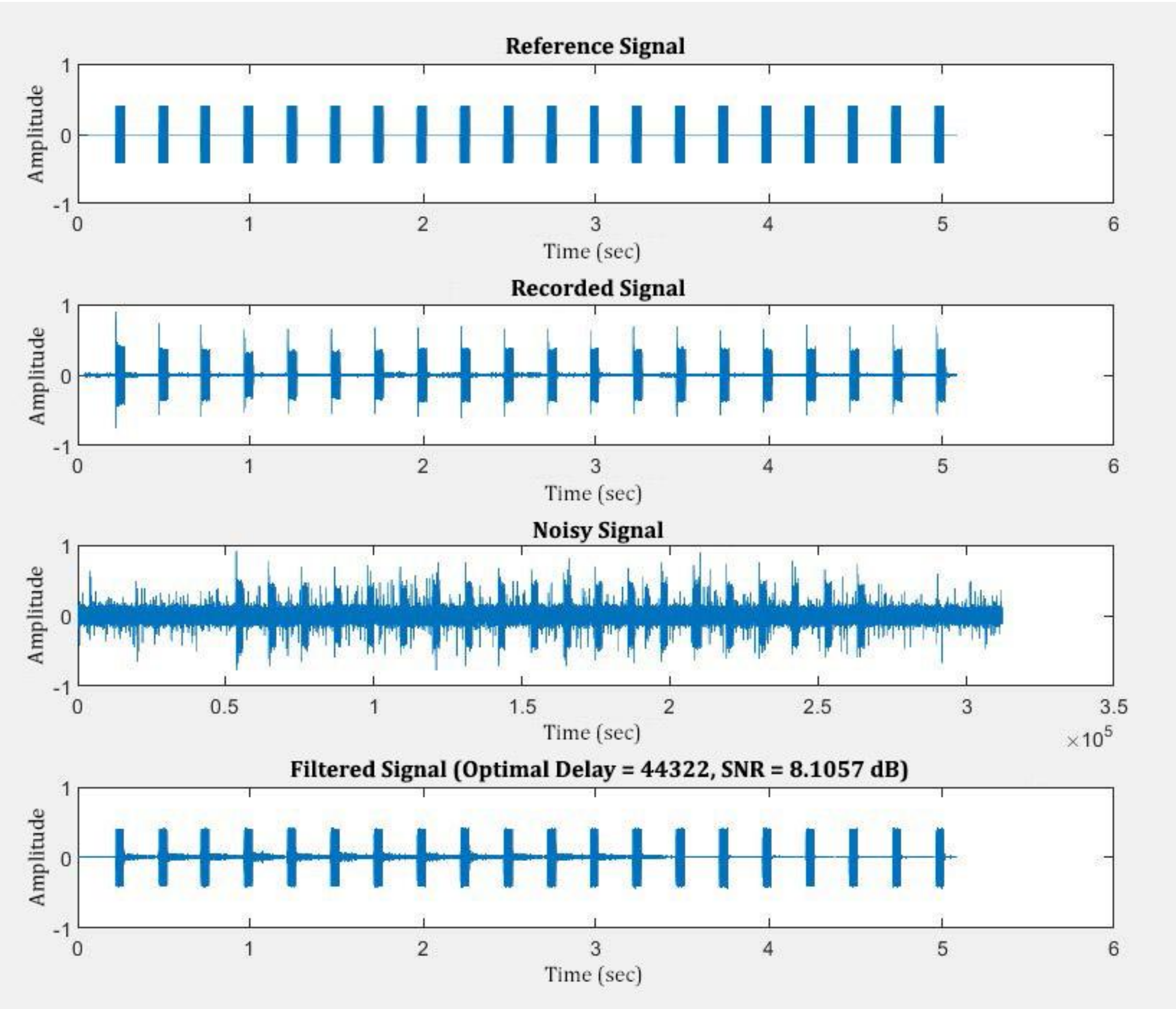

Figure 4. SBES Signal filtering results using LMS filter.

According to The Naval Hydro-Oceanography Center (Pusat Hidro-Oseanografi TNI-AL), accurate depth measurements are vital for national marine charting, supporting navigation safety, and submarine route planning. In defense applications, depth information supports mine avoidance, safe submarine maneuvering, and underwater weapon deployment. These applications require not only accurate echo detection but also robust denoising methods.

In this study, depth measurement determines when the delay or time of the signal bouncing back to the sonar and fast propagation in water is known. From the experimental simulation, a delay was optimally identified at the 44322nd data point. Give a sampling rate of 44100, meaning that in one second there are 44100 data taken, then the signal bounce time is obtained for 1.005 seconds, because this is a reflected signal, the time is divided by 2, so that a time of 0.5025 seconds is obtained with the fast propagation of sea water, for example 1400 m / s so that the depth of sea water is 703.5 meters.

The moving average and moving median filters are two filters that are often used to reduce noise present in signals in time series. They cannot adapt quickly to dynamic changes in data trends because they use a static approach. The moving average filter considers all data points in a moving window to have the same weight, making it unable to capture sudden changes in data patterns, while the moving median uses a static approach in calculating the median, which also hinders its ability to respond quickly to changing trends. The LMS filter is a development of the previous two filters and is a more advanced adaptive technique. LMS can dynamically adjust the filter coefficients based on the filter output error and the desired value, so the LMS filter is more responsive to dynamic changes in data and is better used in complex data. This research still has limitations, one of which is the dependence on learning parameters, which requires careful adjustment to obtain more optimal performance. LMS also still has slow convergence in some situations such as when the data used has a very high variation. Therefore, further development of this method is still needed

This theoretical finding has a great impact on its application to sea defense systems. In submarine navigation, accurate depth measurements are required in order to avoid collisions with the seabed or other objects. In addition, sea defense systems also include minesweeping operations and the ability of sonar to detect high SNR objects, which is crucial in reducing the effect of interference on the marine environment. LMS has become an adaptive method for improving signal clarity and detection accuracy. In Anti-Submarine Warfare (ASW), detecting the presence of an enemy submarine operating covertly is affected by the quality of the sonar signal, which can be assisted by LMS in improving performance in complex acoustic environments. Moreover, Autonomous Underwater Vehicle (AUV) operations also require accurate depth information to determine the success of reconnaissance and seafloor mapping missions. This is an important theoretical discovery in improving the reliability of adaptive sonar systems in strengthening national maritime security and resilience.

CONCLUSION

Underwater depth measurements using acoustic signals from a Single Beam Echosounder (SBES) demonstrate good results after denoising with the Least Mean Square (LMS) algorithm. This method effectively reduces noise without significantly distorting the original signal, resulting in a depth estimation of 703.5 meters. The quality of the denoised signal is further validated by a Signal-to-Noise Ratio (SNR) of 6.7248 dB, indicating accurate and relatively clean signal reconstruction. Acoustic depth signals are often affected by Gaussian and non-Gaussian noise due to environmental factors and sensor limitations. The LMS algorithm has the ability to adapt to signal characteristics, enhancing the reliability of the depth measurements for various applications such as seabed mapping, oceanographic surveys, and military operations.

Future research could focus on developing more advanced adaptive filtering techniques to enhance the system's robustness under various environmental conditions. Additionally, exploring hybrid filtering approaches that integrate LMS with deep learning models or other adaptive algorithms could optimize acoustic signal processing performance. Investigating the real-time implementation of LMS filters in underwater acoustic applications may also improve the accuracy and reliability of sonar-based water surveys, ocean depth measurements, and various scientific, commercial, and military operations.

AUTHOR CONTRIBUTIONS

A.R.A.: Conceptualization, investigation, methodology, software, resources, and writing – original draft. S.Q.A.: Investigation, formal analysis, visualization, and writing – review & editing. A.S.: Supervision, software, writing – review & editing.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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