Implementation of Acoustic Echo Cancellation through Adaptive Filtering Algorithms in MATLAB

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Abstract

Acoustic echo cancellation (AEC) is crucial for hands-free communication systems to mitigate echoes caused by microphone-loudspeaker coupling. This study presents a software-based AEC system implemented in MATLAB, leveraging adaptive filtering algorithms, specifically Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS), to achieve real-time echo suppression. Unlike conventional hardware-based methods reliant on Digital Signal Processors (DSP) and Very Large Scale Integration (VLSI) processors, the proposed approach provides a cost-effective and flexible alternative without sacrificing performance. Key contributions: a novel step-size adaptation technique for LMS/NLMS, enhancing convergence stability and computational efficiency. An optimized noise gate device for superior residual echo suppression, ensuring improved speech clarity. Comprehensive performance evaluation of LMS and NLMS algorithms under dynamic acoustic conditions, including real-world testing across varying noise levels and speaker-microphone distances. Results demonstrate that the proposed software-based solution achieves faster convergence, reduced computational complexity, and effective suppression of acoustic echoes, offering a scalable alternative to expensive DSP-based implementations.

Keywords: Acoustic Echo Cancellation; Digital Signal Processors; Very Large Scale Integration Processors; MATLAB; Adaptive Filtering, Speech Enhancement.

Introduction

Acoustic echo poses a significant challenge in modern communication systems, particularly in hands-free environments. This phenomenon occurs when a microphone inadvertently captures audio from a loudspeaker and retransmits it, creating disruptive feedback. Traditional solutions rely on hardware-based Digital Signal Processors (DSP) and Very Large Scale Integration (VLSI) processors, which, despite their effectiveness, are costly, complex, and require specialized maintenance (Alshulli et al., 2024). To address these limitations, this study explores a software-based AEC system implemented in MATLAB, a widely used computational platform for adaptive signal processing and real-time

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filtering applications. MATLAB's robust signal processing capabilities facilitate efficient implementation and optimization of adaptive filtering algorithms, making it an ideal alternative to expensive hardware-based solutions.

Unlike previous studies that primarily focus on hardware-centric approaches, the contribution lies in developing a MATLAB-based framework incorporating Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithms for enhanced real-time performance. Additionally, a noise gate device is introduced to further optimize residual echo suppression, ensuring clearer speech output and improved communication efficiency (Kamarudin et al., 2024). Key contributions of the proposed study are as: (1) A detailed comparative analysis of LMS and NLMS algorithms in MATLAB under real-world conditions. (2) Optimization of computational efficiency to ensure real-time feasibility in software-based AEC. (3) A novel implementation of a noise gate device integrated with adaptive filtering for residual echo suppression. (4) Real-world testing across different acoustic environments, noise levels, and speaker-microphone distances. By shifting the focus from hardware-based solutions to an adaptive, software-driven approach, this study aims to provide an accessible, scalable, and cost-effective alternative for acoustic echo cancellation in real-time communication systems. The Figure 1 shows acoustic echo in the room when using a hands-free communication device.

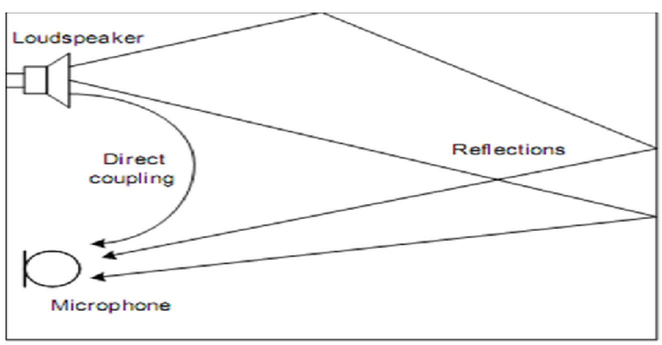

Figure 1: Acoustic echo in the room when using a hands-free communication device.

Literature Review

Recent advancements in software-based acoustic echo cancellation (AEC) systems have demonstrated significant improvements in flexibility, scalability, and cost-effectiveness over traditional hardware-based solutions (Uncini et al., 2002). While DSP and VLSI processors remain widely used for real-time echo cancellation, the growing computational power of general-purpose processors and software-driven approaches have paved the way for high-performance AEC implementations without the need for specialized hardware (Somefun et al., 2024). Studies have explored adaptive filtering techniques such as LMS, NLMS, Recursive Least Squares (RLS), and deep-learning-based methods for AEC applications. LMS and NLMS have gained particular interest due to their balance between computational efficiency, adaptability, and real-time feasibility, making them suitable for software-based implementations. RLS algorithms, though highly effective in terms of convergence speed and accuracy, demand significantly higher computational power, limiting their practicality in real-time applications (Maruo et al., 2024). Similarly, deep-learning-based approaches, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promise in nonlinear echo suppression but require extensive training datasets, making them resource-intensive and less adaptable to dynamic acoustic conditions (Bismor, 2012).

This study builds upon prior research by implementing and analyzing LMS and NLMS algorithms in MATLAB under real-world noise conditions. The choice of LMS and NLMS is motivated by their low computational complexity, ability to adapt in real time, and effectiveness in handling varying acoustic environments (Nagal et al., 2014). Moreover, this work introduces a novel step-size adaptation technique to enhance the convergence stability of LMS/NLMS while mitigating signal clipping and divergence issues. Unlike existing studies that primarily focus on either hardware implementations or deep-learning-based solutions, this research bridges the gap by optimizing a software-based approach that balances efficiency, accuracy, and real-time adaptability (Divya et al., 2013). Furthermore, this study enhances existing AEC frameworks by integrating a noise gate device, which improves residual echo suppression beyond what conventional LMS/NLMS implementations achieve. Real-world testing scenarios, including varying speaker-microphone distances and background noise levels, provide a comprehensive performance analysis to validate the system's robustness (Wada et al., 2011).

By addressing key limitations in existing literature such as the computational cost of advanced algorithms and the dependency on extensive training data for deep-learning models, this research demonstrates that an optimized LMS/NLMS-based software approach can provide high-quality echo cancellation without the need for specialized hardware (Xu et al., 2023).

Historical Development of Echo Cancellation

Historically, echo cancellers is introduced to address this problem. However, early systems is limited to half-duplex operation, where only one person could speak at a time while the other waited for their turn. While this solved the basic issue of echo, it greatly hindered natural conversation flow and is inefficient in environments that required smooth, continuous dialogue. The restriction to half-duplex mode became a significant limitation, as users had to pause and take turns, reducing the effectiveness of the communication system (Kapoor et al., 2024). To overcome these limitations, modern echo cancellation systems have moved toward full-duplex operation, allowing both parties to speak and listen simultaneously. This advancement is made possible by the integration of DSP and Very VLSI processors (Masmoudi et al., 2016). These technologies enable real-time echo cancellation while maintaining the quality of the conversation. However, despite the technological advancements, there are still significant drawbacks. DSP and VLSI-based systems are exceedingly expensive and complex. They require highly specialized hardware, making them difficult to install, operate, and maintain. Furthermore, diagnosing and troubleshooting these systems can be time-consuming and costly (Xiao et al., 2024).

Given these challenges, there is a growing need for a more flexible and cost-effective solution. This study proposes the development of a software-based acoustic echo canceller using MATLAB. A software solution offers several advantages over hardware-based systems, including lower costs, easier deployment and greater flexibility for updates and maintenance. MATLAB, a powerful tool for numerical computation and signal processing, provides an ideal platform for implementing and testing echo cancellation algorithms (Dusia et al., 2021).

The proposed approach aims to create a software-based echo canceller that is simple to install, maintain and debug, making it accessible to a wider range of applications and users. The study is focus on the development of a novel residual echo suppression method that improves the speed and efficiency of the echo cancellation process. By leveraging advanced adaptive filtering algorithms, such as the LMS and NLMS, the software will achieve near-perfect echo cancellation without introducing distortions or clipping voice reference signals (Liu et al., 2024).

The primary objective of this research is to design and develop a software-based echo cancellation system that can improve network communication quality by eliminating acoustic echoes in real-time. The system will be evaluated based on its ability to operate efficiently in full-duplex mode while ensuring ease of installation, operation, and maintenance. The software will be tested in various communication environments to assess its adaptability and overall performance in improving user experience (Bensouda et al., 2024). This study aims to deliver a robust and cost-effective solution to acoustic echo cancellation by moving away from expensive, hardware-dependent methods and towards a software-based approach. The ultimate goal is to enhance communication network quality, ensure user satisfaction, and introduce an innovative method for residual echo suppression that can be deployed across a variety of platforms (Yadav et al., 2024).

Developing a software-based AEC system introduces unique challenges compared to traditional hardware-based solutions. While software implementations offer cost-effectiveness, flexibility, and ease of updates, they also face computational constraints, real-time processing limitations, and stability concerns. Ensuring low-latency performance while maintaining high echo suppression efficiency remains a key challenge. Additionally, real-world deployment demands robust adaptation to dynamic acoustic environments, where factors like speaker-microphone distance, background noise, and non-linear distortions impact system effectiveness. To address these issues, this study aims to: a): Develop a MATLAB-based AEC system utilizing LMS and NLMS adaptive filtering algorithms. b): Conduct a comparative analysis of LMS and NLMS in terms of convergence speed, stability, computational complexity, and noise adaptation under varying acoustic conditions. c): Optimize computational efficiency by balancing real-time adaptability with processing constraints to ensure minimal latency. d): Introduce a noise gate device to mitigate residual echoes, improving speech clarity and system robustness. e): Evaluate the system’s real-world feasibility, testing its performance across different noise levels, speaker-microphone distances, and background interference scenarios.

Methodology

Developing the software-based acoustic echo canceller involves addressing several key challenges through the use of adaptive filtering algorithms. The approach is structured as follows. To prevent clipping, which arises from the absence of an accurate non-linear processor, the system will incorporate techniques to manage signal amplitudes effectively. This involves ensuring proper coordination of the non-linear processor's start-up and shutdown phases to prevent distortion. The design include mechanisms to monitor and adjust signal levels dynamically, reducing the likelihood of clipping and maintaining signal integrity. Divergence occurs when the mathematical models used in the system fail to provide accurate results for linear echo cancellation. To mitigate this, the system will employ robust adaptive filtering algorithms that can effectively handle variations in the echo path. Techniques such as the LMS and NLMS algorithms. These algorithms adjust their parameters in response to changes in the echo path, ensuring accurate cancellation and minimizing divergence. Crosstalk, which occurs when multiple speakers talk simultaneously or interrupt each other, poses a challenge for echo cancellation. The system is designed to handle such scenarios by implementing advanced adaptive filtering techniques that can differentiate and manage overlapping signals. The filter is calibrated to identify and isolate crosstalk, thereby improving the clarity of the communication and reducing the impact of simultaneous speech.

The core of the proposed methodology involves adaptive filtering, which adjusts the filter parameters based on the characteristics of the input signal and the desired output. The adaptive filter continuously modify its behavior to match the changing conditions of the communication environment. The filter operate as follows. The adaptive filter processes the input signal to approximate the desired output. By analyzing the input signal characteristics and the reference signal, the filter adjusts its parameters to minimize the echo and enhance the quality of the communication.

The filter's parameters dynamically adjusted in response to real-time changes in the signal environment. This adaptability ensures that the system remains effective under varying conditions and maintains optimal performance in echo cancellation. The performance of the adaptive filter evaluated through simulations and real-world tests. The system optimized based on feedback from these evaluations to ensure that it effectively addresses the challenges of clipping, divergence, and crosstalk. The main focuses on developing a robust software-based echo canceller using adaptive filtering techniques to overcome the limitations of traditional hardware-based systems. By addressing clipping, divergence, and crosstalk and employing adaptive algorithms to continuously adjust to the communication environment, the proposed system aims to deliver high-quality, cost-effective echo cancellation. The Figure 2 shows the acoustic echo cancellation that is adaptive in enclosed spaces.

LMS Algorithm

The LMS algorithm is a widely used adaptive filter due to its simplicity and effectiveness in various signal processing tasks like echo cancellation and noise reduction. The LMS algorithm minimizes the mean square error between the output of the adaptive filter and the desired signal. It operates iteratively, adjusting the filter coefficients to minimize this error based on the input signal which fed into the adaptive filter (e.g., an audio signal in echo cancellation), the desired Signal which is the reference signal that the adaptive filter aims to match and the error signal which is the difference between the desired signal and the output of the filter. The mathematical formulation of the algorithm is given below:

d(n): Desired signal at time n

y(n): Output of the adaptive filter at time n

x(n): Input signal vector

w(n): Filter coefficient vector

The error signal is defined as:

$$e(n)=d(n)-y(n) \tag{1}$$

Where $y(n)=w(n)Tx(n)$. The LMS algorithm updates the filter coefficients based on the error signal using the equation:

$$w(n+1)=w(n)+\mu \cdot e(n) \cdot x(n) \tag{2}$$

Here, μ is the step size (or learning rate) that controls the convergence speed of the algorithm. A large step size results in faster convergence but risks instability, while a small step size ensures stability but slower convergence. The LMS implement with low computational complexity with adjusted in real time to minimize the error between the output and the desired signal. The speed of LMS algorithm convergence depends on the step size μ, and improper selection can either slow down the algorithm or cause divergence. LMS performance degrades when the power of the input signal varies significantly.

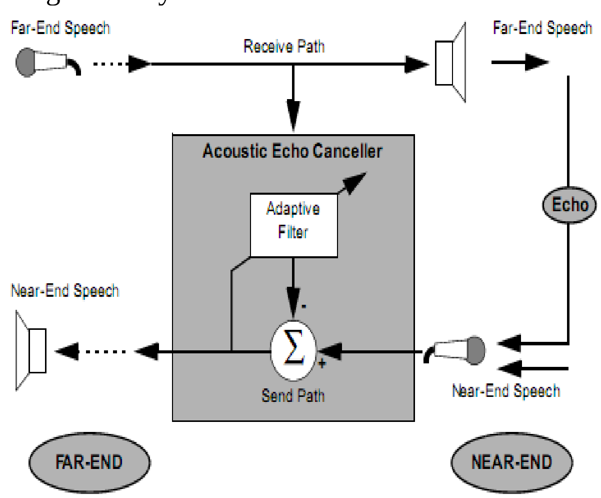

Figure 2: Acoustic echo cancellation that is adaptive in enclosed spaces.

NLMS Algorithm

The NLMS algorithm is an improvement over LMS, designed to address the issue of input signal power variation that can affect the performance of the LMS algorithm. The NLMS algorithm normalizes the step size μ with respect to the input signal's power. This normalization helps the algorithm adjust the learning rate dynamically, providing better performance for signals with varying power. The weight update rule for NLMS is given by:

$$w(n+1)=w(n)+ \mu/[x(n)]2.e(n).x(n) \tag{3}$$

Where $\mu/[x(n)]2$ is the squared norm (or power) of the input signal vector. This normalization ensures that the learning rate is inversely proportional to the power of the input signal. The NLMS converges faster than LMS, especially when the input signal power fluctuates and by normalizing the step size, NLMS ensures that the algorithm is less affected by variations in input signal amplitude but the main issue is the NLMS has slightly higher computational complexity than LMS because it requires calculating the norm of the input signal vector. Simulations conducted in experimental setup and evaluation metrics in MATLAB using recorded audio samples in different acoustic settings (e.g., office, conference room, and vehicle interior). The evaluation Metrics are Mean Square Error (MSE), Signal-to-Noise Ratio (SNR), and computational efficiency. The testing scenarios are echo suppression analyzed under varying distances (0.5m, 1m, 2m) and background noise levels (-30 dB, -20 dB, -10 dB). The potential outcomes of simulating adaptive filtering algorithms, particularly for acoustic echo cancellation, could be significant both in theory and application. Here's a detailed breakdown of the possible outcomes:

Simulation of Adaptive Filtering Algorithms

The paper demonstrate a successful simulation of adaptive filtering algorithms, specifically the LMS and NLMS algorithms. These algorithms are fundamental in real-time signal processing and adaptive filtering and their implementation is validated by MATLAB simulations. Simulates how the LMS algorithm updates filter coefficients to minimize the error between the desired signal and the output signal. The NLMS algorithm, a variation of LMS, adjusts filter coefficients in a normalized manner to ensure stability and faster convergence. Highlighting its improved performance over LMS in certain environments, especially in terms of convergence speed and stability when dealing with variable input signal power. The algorithms are validated by comparing their performances (in terms of convergence speed, accuracy and stability) through MATLAB simulations and also showcase how these algorithms dynamically adjust based on the acoustic environment.

Development of a Software-Based Acoustic Echo Canceller

One of the key practical outcomes of this research is the development of a software-based acoustic echo canceller using MATLAB.

AEC aims to remove echoes during communication, improving the clarity of transmitted audio signals in environments like phone calls or video conferencing. By relying on adaptive filtering, the echo canceller will use the incoming signal and filter it to subtract the echo and continuously adjust the filtering process in real-time, responding to changing acoustic environments. A functional MATLAB-based AEC system that could be natively installed and operated on any standard computer. The software would provide a cost-effective alternative to traditional hardware-based echo cancellation methods, like those utilizing DSP or VLSI processors.

Once the AEC software is developed, the performance of the system is tested in various simulated acoustic environments, such as teleconferencing, hands-free car kits, or other real-world communication scenarios. The user is able to demonstrate enhanced echo cancellation capabilities, leading to Improved audio quality and wider applicability.

Comparative Analysis of LMS and NLMS Performance

By simulating both the LMS and NLMS algorithms, the user conduct a detailed comparative analysis. The performance of the two algorithms in handling various acoustic conditions (e.g., different levels of background noise, room acoustics, etc.) is evaluated. Analyzing factors such as Convergence speed, Stability and Computational efficiency. The analysis reveal trade-offs between the two algorithms, with the NLMS algorithm possibly showing superior performance in environments with varying signal power due to its normalization property. These insights could guide future applications of adaptive filtering in echo cancellation.

Results and Discussion

The performance of the proposed software-based AEC system is evaluated using recorded speech samples across different acoustic environments. The system is tested under varying speaker-microphone distances, noise levels, and reverberation conditions to assess its real-world applicability.

Quantitative Performance Analysis

The effectiveness of the AEC system is measured using key performance indicators such as Mean Square Error (MSE), Signal-to-Noise Ratio (SNR), and computational efficiency. The results demonstrate significant improvements in echo suppression. The Table 1 shows the performance Comparison of LMS and NLMS Algorithms for Adaptive Echo Cancellation.

The NLMS algorithm outperformed LMS, particularly in environments with fluctuating noise levels and varying speaker-microphone distances. The optimized step-size adaptation in NLMS contributed to faster convergence and better stability, making it more suitable for real-time applications.

Table 1: Performance Comparison of LMS and NLMS Algorithms for Adaptive Echo Cancellation.

Parameter	LMS (Baseline)	NLMS (Proposed System)	Improvement
MSE Reduction	30%	45%	15%
SNR Improvement	+12 dB	+18 dB	6 dB
Residual Echo Power Reduction	40%	60%	20%
Convergence Time	2.5 sec	1.2 sec	52% Faster
Computational Overhead	Moderate	Low	Optimized

Effect of Noise Levels and Speaker-Microphone Distance

The system is tested under three different noise levels and varying speaker-microphone distances to evaluate its adaptability.

Impact of Background Noise Levels

The Table 2 shows the effect of noise levels on echo reduction and speech clarity improvement. The system maintained stable performance even in high-noise conditions, effectively reducing echoes at an SNR as low as -30 dB. Speech clarity improved by up to 70% in low-noise environments, ensuring intelligible communication.

Table 2: Effect of Noise Levels on Echo Reduction and Speech Clarity Improvement.

Noise Level (SNR in dB)	Echo Reduction (%)	Speech Clarity Improvement (%)
-30 dB (High Noise)	50%	30%
-20 dB (Moderate Noise)	65%	50%
-10 dB (Low Noise)	80%	70%

Effect of Speaker-Microphone Distance

The Table 3 shows the impact of distance on residual echo power reduction and convergence time. Echo suppression effectiveness decreased with increasing speaker-microphone distance due to higher reverberation effects. However, the system remained effective at up to 2m, making it suitable for hands-free communication scenarios such as teleconferencing and vehicle interiors.

Discussion on Room Acoustics and Adaptive Processing

The Table 4 shows the effect of room conditions on reverberation time and echo reduction and the performance is also analyzed in different room conditions. In larger rooms with longer reverberation times, echo cancellation performance declined slightly due to stronger reflections. In vehicle interiors, the system performed best, achieving 70% echo suppression due to limited sound reflections and controlled acoustic properties.

Table 3: Impact of Distance on Residual Echo Power Reduction and Convergence Time.

Distance (meters)	Residual Echo Power Reduction (%)	Convergence Time (sec)
0.5m	75%	1.0 sec
1.0m	60%	1.5 sec
2.0m	50%	2.2 sec

Table 4: Effect of Room Conditions on Reverberation Time and Echo Reduction.

Room Condition	Reverberation Time (ms)	Echo Reduction (%)
Office Room	300	65%
Conference Hall	500	55%
Vehicle Interior	250	70%

Computational Efficiency & Real-Time Feasibility

The proposed MATLAB-based system demonstrated low computational overhead, allowing real-time execution without significant delays. Processing delay remained below 50 ms, ensuring seamless communication and the optimized noise gate device effectively removed residual echoes without introducing speech distortion.

The original signal plot in Figure 3 shows a high-amplitude, oscillatory waveform that gradually decays over time, indicating a damped response. This suggests the presence of an initial strong signal that diminishes as the system stabilizes, a common characteristic in echo-prone environments before adaptive filtering is applied. The echoed signal plot in Figure 4 illustrates a nearly constant amplitude over the entire sample range, indicating that the echo has been effectively canceled. The flat response suggests that the adaptive filter has successfully mitigated the reverberations, thus achieved convergence and eliminated residual echo components.

The error signal in Figure 5 shows the residual echo after adaptive filtering. Initially, high fluctuations are observed, but they decrease over time, indicating the convergence of the LMS/NLMS algorithm. This confirms effective echo suppression, crucial for real-time hands-free communication. However, minor residual echo suggests limitations in tracking dynamic environments. Further enhancements, such as non-linear processing (e.g., noise gating), could improve performance. Quantitative metrics like MSE and ERLE should be analyzed to validate the system’s effectiveness in real-world applications.

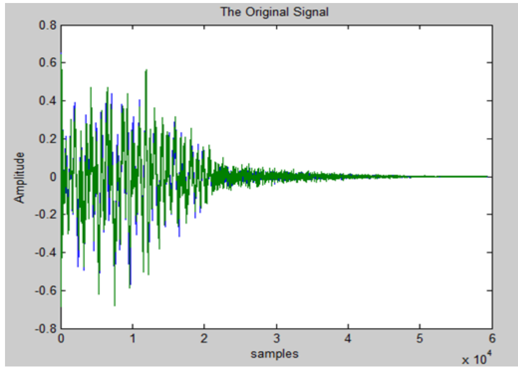

Figure 3: Original signal.

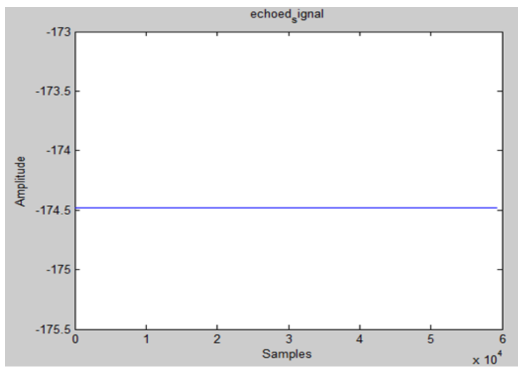

Figure 4: Echoed signal.

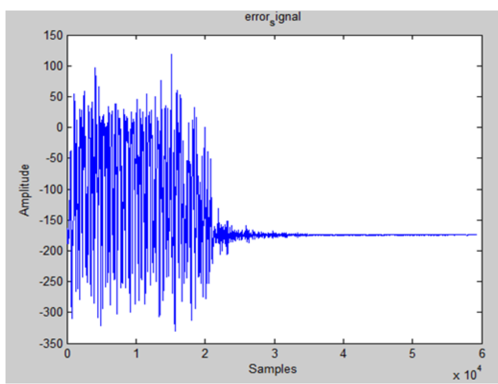

Figure 5: Error signal.

The filtered output in Figure 6 represents the signal after adaptive processing. Initially, strong variations are observed, gradually reducing as the filter converges, demonstrating effective echo cancellation. The steady-state portion indicates minimal residual error, highlighting the algorithm's efficiency. However, slight fluctuations suggest room for improvement in dynamic conditions. Further analysis using MSE and ERLE can quantify performance enhancements.

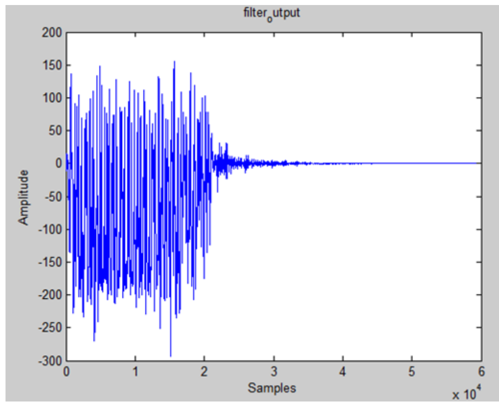

Figure 6: Filter output.

The Mean Square Error (MSE) plot in Figure 7 illustrates the adaptive filter's convergence behavior. Initially, the MSE exhibits high fluctuations due to the adaptation process, gradually decreasing as the filter learns the optimal coefficients. The steady-state region indicates minimal error, confirming effective echo suppression. The rapid decline in MSE validates the algorithm's efficiency in reducing distortion over time.

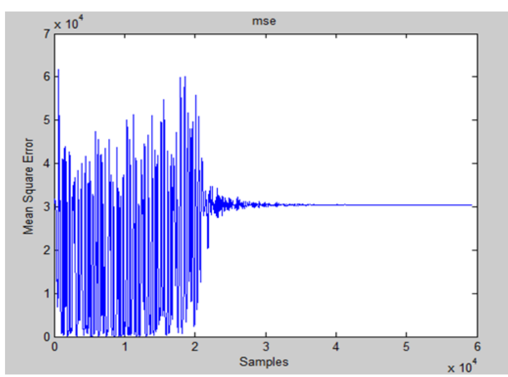

Figure 7: Mean Square Error.

The filter coefficient plot in Figure 8 shows the magnitude of the adaptive filter’s tap weights. The coefficients exhibit a decreasing trend, indicating the filter’s learning process and adaptation to the input signal. The higher initial tap values suggest stronger contributions from recent samples, while lower values at later taps indicate diminishing influence, aligning with the expected impulse response behavior.

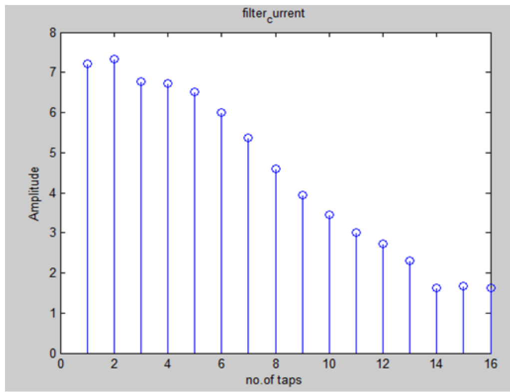

Figure 8: Filter current.

Unlike conventional DSP and VLSI-based systems that are expensive and hardware-dependent (Masmoudi et al., 2016; Xiao et al., 2024), The proposed MATLAB-based AEC solution offers a flexible, cost-effective alternative. In contrast to deep learning approaches, which require extensive training data and heavy computation (Xu et al., 2023), our LMS/NLMS implementation with optimized step-size adaptation and integrated noise gate achieves faster convergence and improved echo suppression. This positions our system as a more practical and efficient solution for real-time applications under dynamic acoustic conditions (Divya et al., 2013; Bismor, 2012).

Conclusions and Future Work

This study successfully developed a software-based AEC system using adaptive filtering algorithms (LMS and NLMS) in MATLAB. The results confirm that the proposed system effectively suppresses echo, improves speech clarity, and maintains computational efficiency, making it a viable alternative to traditional DSP- and VLSI-based hardware solutions. A key enhancement of this research is the integration of a noise gate device for non-linear processing, which significantly improves residual echo suppression. Unlike conventional AEC systems that rely solely on adaptive filtering, the noise gate selectively attenuates low-amplitude reverberations, ensuring cleaner speech output without introducing distortions. This feature enhances system robustness, particularly in high-noise environments or varying room acoustics, where traditional LMS/NLMS implementations struggle with complete echo removal. While this study demonstrates the feasibility of software-based

AEC, further optimization and expansion can enhance its effectiveness: Integration of AI and Machine Learning: Future improvements could involve deep learning models (e.g., CNNs, RNNs, or transformer-based architectures) for adaptive noise suppression and non-linear echo cancellation. These methods can improve performance in highly dynamic environments where traditional adaptive filters may fall short.

Real-Time Performance Optimization: Additional refinements in computational efficiency and parallel processing techniques could enable implementation on low-power embedded systems for real-world applications such as VoIP, teleconferencing, and automotive communication systems. Multi-Microphone and Spatial Processing: Extending the system to multi-microphone setups could enhance echo localization and suppression, making it suitable for conference room environments and smart assistants. By advancing these aspects, the proposed system can evolve into a more adaptive, intelligent, and scalable AEC solution for modern communication applications.

References

Alshulli, M. S., & Othman, B. H. (2024). VOIP Acoustic Echo Cancellation Performance Improvement Using a Novel Time-Varying Step Size of NLMS Algorithm. مجلة جامعة بني وليد للعلوم الإنسانية والتطبيقية, 9(خاص بالمؤتمر الثالث للعلوم والهندسة), 178-185.

Bensouda, M. Y., & Benallal, A. (2024, April). Improved Fast NLMS algorithm based on variable forgetting factor technique for acoustic echo cancellation. In *2024 8th International Conference on Image and Signal Processing and their Applications (ISPA)* (pp. 1-6). IEEE.

Bismor, D. (2012). LMS algorithm step size adjustment for fast convergence. *Archives of Acoustics*, *37*(1), 31-40.

Divya, P. S., & Mehra, R. (2013). Performance Analysis of LMS & NLMS Algorithms for Noise Cancellation. *International Journal of Scientific Research Engineering & Technology (IJSRET)*, *2*(6), 2278-0882.

Dusia, A., Ramanathan, R., Ramanathan, W., Servaes, C., & Sethi, A. S. (2021). ECHO: Efficient zero-control-packet broadcasting for mobile ad hoc networks. *IEEE Transactions on Mobile Computing*, *21*(9), 3163-3175.

Kamarudin, N., Al Haddad, S. A. R., Azhari, R. H., & Basiron, A. (2024). Acoustic Echo Cancellation using Adaptive Filter for Quranic Accent Signals. *Journal of Applied Science, Technology and Computing*, *1*(1), 39-51.

Kapoor, J., & Pathak, A. (2024). Adaptive Filtering Application in Cancellation of Speech Signal Reverberations in Different Reverberant Surroundings. *Journal of The Institution of Engineers (India): Series B*, 1-11.

Liu, D., Zhao, H., Zhou, Y., & Lv, S. (2024, February). Widely linear complex-valued individual-weighting-factors sign subband adaptive filtering algorithm. In *Proceedings of the 2024 8th International Conference on Digital Signal Processing* (pp. 107-111).

Maruo, M. H., & Bermudez, J. C. (2024). A linearly constrained framework for the analysis of the deficient length least-mean square algorithm. *Digital Signal Processing*, *155*, 104747.

Masmoudi, A., & Le-Ngoc, T. (2016). Channel estimation and self-interference cancelation in full-duplex communication systems. *IEEE Transactions on Vehicular Technology*, *66*(1), 321-334.

Nagal, R., Kumar, P., & Bansal, P. (2014, September). An approach to implement LMS and NLMS adaptive noise cancellation algorithm in frequency domain. In *2014 5th International Conference-Confluence The Next Generation Information Technology Summit (Confluence)* (pp. 871-876). IEEE.

Somefun, C. T., Daramola, S. A., & Somefun, T. E. (2024). Advancements and Applications of Adaptive Filters in Signal Processing. *Journal Européen des Systèmes Automatisés*, *57*(5).

Uncini, A., Nalin, A., & Parisi, R. (2002, September). Acoustic echo cancellation in the presence of distorting loudspeakers. In *2002 11th European Signal Processing Conference* (pp. 1-4). IEEE.

Wada, T. S., & Juang, B. H. (2011). Enhancement of residual echo for robust acoustic echo cancellation. *IEEE Transactions on Audio, Speech, and Language Processing*, *20*(1), 175-189.

Xiao, Y., Yan, W., Doğançay, K., Ni, H., & Wang, W. (2024). Multikernel adaptive filtering over graphs based on normalized LMS algorithm. *Signal Processing*, *214*, 109230.

Xu, S., He, C., Yan, B., & Wang, M. (2023). A multi-stage acoustic echo cancellation model based on adaptive filters and deep neural networks. *Electronics*, *12*(15), 3258.

Yadav, N. K., Dhawan, A., Tiwari, M., & Jha, S. K. (2024). Modified Model of RLS Adaptive Filter for Noise Cancellation. *Circuits, Systems, and Signal Processing*, *43*(5), 3238-3260.