Design and Implementation of Hybrid Adaptive Noise Canceller for Audio Signal Processing

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Abstract — An adaptive filter is a self-adjusting digital signal processor that minimizes error signals and adapts to dynamic environments. It uses algorithms like Least Mean Squares (LMS) and Recursive Least Squares (RLS) for tasks like noise cancellation and system identification. Traditional adaptive algorithms are effective with Gaussian noise but struggle with sudden disruptions. This research focuses on developing robust adaptive filters to manage various noise types, utilizing MATLAB models that demonstrate superior performance in real-time applications. For creating noisy signals four types of noises considered AWGN (Additive White Gaussian Noise), Johnson, random and uniform are considered. A hybrid LMS-RLS filter combines the stability of LMS with the quick response of RLS, performing better in non-stationary conditions with improved precision and reduced computational demand.

Keywords: LMS, NLMS, RLS, MSE, MAE, SNR, PSNR, AWGN

I. Introduction

Traditional adaptive filters, such as Least Mean Squares (LMS) and Normalised LMS (NLMS), face challenges with non-Gaussian noise, particularly when it is impulsive and changes rapidly. Impulsive noise is characterized by sudden spikes and exhibits a heavy-tailed distribution, significantly disrupting signal readings. This can result in slow convergence, high steady-state error, and instability in filtering methods. Research focuses on developing robust adaptive filters that incorporate robust statistics and optimization theory to mitigate the adverse effects of outliers and disturbances, maintaining convergence speed, stability, and accuracy. The chapter discusses foundational concepts, significance, and challenges in creating adaptive filters suited for handling impulsive noise, paving the way for further research.

Adaptive filters are crucial in modern signal processing and communication systems as they can dynamically adjust their coefficients based on varying input signals and environments. Unlike fixed filters, adaptive filters do not require prior knowledge of the signal or noise and progressively minimize error measures, such as mean squared error (MSE), to enhance output accuracy. Their versatility enables applications such as echo and noise cancellation, system identification, channel balancing, biological signal processing, and radar systems.

II. About adaptive filters

An adaptive filter combines a linear filter with a variable transfer function, allowing parameter adjustments through optimization methods. Digital filters are the most prevalent type, particularly in scenarios where some processing elements are unpredictable, such as reverberant environments with mirrored surfaces.

The closed-loop adaptive filter improves its performance by using an error signal input to adjust the transfer function via a cost function, often defined as the square of the mean error signal. The rise in digital signal processor capabilities has led to widespread adoption of adaptive filters in devices such as digital cameras, camcorders, phones, and medical monitoring systems.

III. Motivation

The main Motivation for the need to create flexible filters that can handle sudden noise is because standard algorithms do not function effectively in the real world. Impulsive noise in the communications industry could be caused by switching devices or electromagnetic radiation. As a result, the system becomes less reliable and produces erroneous data bursts (Zhang et al., 2019). Artifacts in electrocardiogram (ECG) or electroencephalogram (EEG) data may resemble impulsive noise in biological settings. Thus, to preserve the integrity of the signal without introducing distortion, strong adaptive filtering is necessary (Li & Ding, 2020).

Furthermore, heavy-tailed noise distributions pose a problem for industrial applications such power line communications and tracking devices. These noise distributions are difficult for standard MSE-based adaptive filters to manage (Bouboulis et al., 2011). Accordingly, two fundamental properties are required for an adaptive filter to be deemed robust:

1) It must be immune to severe outliers
2) It must still be able to quickly react to real changes in the signal. The current research on robust adaptive filtering focuses on finding this equilibrium.

IV. Literature survey

[1] André & De Lamare, Rodrigo. (2025), In this work, we present a reliable adaptive filtering method for active noise control in the presence of impulsive noise, known as the filtered-x hyperbolic tangent exponential generalized Kernel M-estimate function (FXHEKM). The algorithm is statistically analyzed, and its computational cost is assessed. Using mean-square error (MSE) and average noise reduction (ANR) metrics, the FXHEKM algorithm demonstrates effectiveness in eliminating additive spurious signals, such as α-stable noises, compared to similar techniques.

[2] Liu et.al (2024) This study investigates robust adaptive algorithms for suppressing impulsive noise, categorizing methods based on algorithmic considerations such as cost functions, step sizes, sparsity, and outlier removal. Liu describes flexible filtering strategies for various noise circumstances, analyzing the pros and cons of each approach. The work addresses both theoretical and practical

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challenges, including system convergence and resilience, which are critical for academics aiming to develop or enhance filtering algorithms. It also highlights the need for further research into methods that balance convergence speed and noise resilience in real-time applications, particularly for adaptive filtering in non-Gaussian noise settings.

[3] Abdelrhman et al. (2023) A novel half-quadratic criterion (HQC) adaptive filtering approach utilizes a convex cost function to effectively address fast noise impacts by removing outliers in noisy signals. This method offers enhanced accuracy and reliability over traditional least squares adaptive filters, particularly during abrupt signal changes. Research indicates that the HQC-based filter minimizes steady-state misadjustment and maintains performance across different noise levels. This innovation significantly boosts noise resistance in adaptive filtering, with potential applications in telecommunications, radar, and biomedical signal processing, improving real-world signal processing resilience.

[4] Alanazi et al. (2023) suggested A novel real-time adaptive filtering method effectively removes rapid, high-density noise, enhancing the quality and reliability of photographs. This is particularly critical in medical diagnostics, where signal integrity is vital for decision-making. The system outperforms traditional filtering techniques by responding in real-time and withstanding abrupt disruptions, which often compromise image quality in conventional methods. The findings indicate that adaptive filters targeting impulsive noise can significantly improve the signal-to-noise ratio (SNR) and reduce distortion, making this approach applicable to imaging modalities such as CT, MRI, and ultrasound. The study bridges the gap between theoretical filter design and practical implementation in medical settings, emphasizing the importance of robust algorithms in critical environments.

[5] Wenqi & Chien, Ying-Ren. (2023) When applied to nonlinear systems, kernel adaptive filters (KAF) enhance traditional adaptive filter performance, although impulsive noise can degrade their effectiveness. To mitigate this issue, the modified-sign least-mean-square method (KMSLMS), known as the NICE-KMSLMS algorithm, incorporates the nearest-instance-centroid estimation (NICE) strategy to reduce computational costs. Simulations indicate that KMSLMS can lower testing mean-squared error (MSE) by 2.32 dB for nonlinear channel equalization and 7.39 dB for Mackey-Glass chaotic series prediction compared to traditional kernel least-mean-square methods, achieving a 55% reduction in computational cost despite a minor increase in MSE.

[6] Lingling & Shi, Juan. (2021) Self-interference (SI) arises from simultaneous transmission and reception within a system, complicated by impulsive noise and a moving SI channel. This study proposes an adaptive digital SI cancellation method using an improved normalized sub-band adaptive filtering (NSAF) algorithm, which incorporates an arctangent cost function and the sparsity of the SI channel. The algorithm minimizes weight vector updates during impulsive noise and reduces iteration errors. It adjusts the weight vector based on the estimated sparsity of the SI channel at each iteration. Theoretical analysis of computational complexity and convergence is included, with simulation results indicating that the proposed algorithm outperforms existing methods.

[7] Yang & Zhang, Zhiguo. (2021) To address the limitations of frequency range and precision in weak signal collection, this study introduces a weak signal acquisition system utilizing an adaptive filter. The filter adapts to input signal frequency variations through hardware-adjustable narrowband filtering, allowing it to manage high dynamic fluctuations and effectively filter weak signals in noisy environments. Techniques such as digital low-pass filtering and adaptive correction enhance the precision of signal acquisition. Test results confirm that the adaptive filter meets design specifications and successfully captures weak signal data.

[8] Yukun & Ye, Tiangui. (2021) Research focuses on active noise control methods to reduce Gaussian noise, which struggle with impulsive or non-Gaussian noise. The filtered-x affine projection sign algorithm, supplemented by a post-adaptive filter, can diminish impulsive noise. A new approach using a convex combination with a variable step size is proposed to enhance this algorithm's performance. This method utilizes a linear function relating the estimated error and desired signal instead of a fixed step size. Full derivation of the recommended algorithms is provided, along with computational complexity analysis. Numerical simulations demonstrate the proposed algorithms' effectiveness in reducing impulsive noise, showing that the variable step size method outperforms the traditional filtered-x affine projection sign algorithm in convergence performance.

V. METHODOLOGY

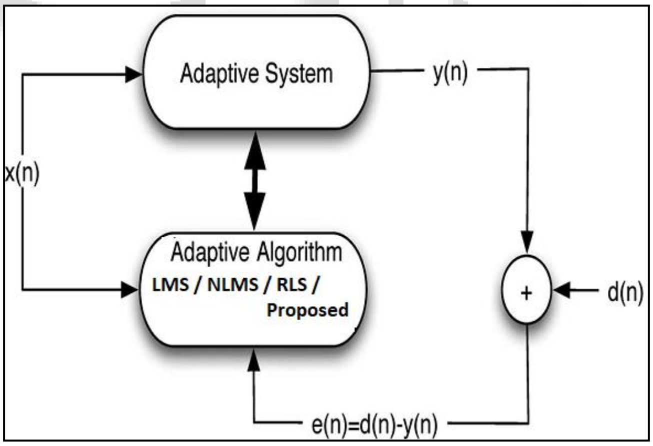

Fig. 1: Basic Block Schematic of the Adaptive Filter

This diagram in Figure 1 illustrates how the primary functioning elements link to one another and interact with one another. Among the components that comprise the system are an error detection block, an adaptive filter, an incoming signal, and a desired or reference signal. These are only few of the components as well. An output is produced by the adaptable filter when it receives a signal and transforms it into an output. Following that, this result is compared to the signal that is intended to be a mistake signal. The adaptive algorithm will continue to update and modify the filter coefficients until the error is as low as it can possibly be. This occurs whenever the algorithm receives the error signal. It is possible for the

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system to function at its optimal level even when the settings are being altered because it constantly modifies the filter factors based on the input received in real time. There are a number of things that need to be achieved with it, including the elimination of noise, the identification of systems, and the enhancement of sound or messages.

A. Traditional Audio Noise Cancellation Filters

1) LMS algorithm:

Due to the fact that it makes use of the error_signal in order to compute the filter coefficients, the LMS is considered to be one of the most straightforward algorithms that are utilised in adaptive structures. It is possible to get the output y(n) of the FIR filter structure by using equation (1).

$$y(n) = \sum_{m=0}^{N-1} \mathrm{w(m)}\ \ \mathrm{x(N-m)} \qquad (1)$$

describes the output y(n) of a Finite Impulse Response (FIR) filter at time n, Where
n is no. of iteration
y(n) : output at time n .
N : filter coefficients or taps.
w(m) : The filter coefficient (or weight) for the m -th tap.
x(n - m) : The input_signal value at time N - m

2) NLMS algorithm:

This problem becomes apparent when the algorithm is used. For the purpose of resolving this challenge, we may make use of the NLMS method, which stands for the Normalised Least Mean Square. The weight vector w(n) is "normalised" at iteration n+1 in relation to the squared Euclidian norm of the input vector x(n) at iteration n. This is carried out to guarantee the validity of the correction.

One possible interpretation of the NLMS method is μ is calculated using equation (4).

$$\mu\,(n) = \frac{\alpha}{c+||x(n)||^2} \qquad (4)$$

describes a variable step size mu(n) used in adaptive filtering algorithms like the NLMS.
μ(n) : The step size at time n . It determines how much the filter weights are adjusted during each update.
α : A +ve constant that controls the overall magnitude of the step size.
c : A small positive constant to prevent division_by_zero and control the adaptation behavior.
|x(n)|^2: The squared magnitude of the input signal time n

3) RLS algorithm:

The RLS algorithms are well-known for their exceptional performance when operating in settings that change in time; however, this comes at the expense of an increased computational complexity and certain stability issues. For the purpose of this procedure, the filter tap weight vector is modified by means of equation (6).

$$w(n) = w^{-T}(\mathrm{n\text{-}1}) + \mathrm{k(n)}\ \ e_{n-1}(n) \qquad (6)$$

describes a weight update rule in adaptive filtering, specifically a form of recursive or iterative update.
w(n): The weight @ step n.
w^T(n-1): The transpose of the weight from the previous time step n-1. This is the current estimate of the weights before updating.
k(n): A gain factor or step size at time n, which determines how much the weights are adjusted based on error.
e{n-1}(n): The error_signal at time n-1.

In accordance with Equation (7), the filter output is computed by using the filter tap weights from the previous iteration in conjunction with the current input vector. Certainly! The two equations you've provided are common in adaptive filtering and signal processing, specifically in the context of estimating signals and errors.

$$y_{n-1}(n) = w^{-T}(n-1)\ \mathrm{x(n)} \qquad (7)$$

y_{n-1}(n): This is the estimated output of the system at time \(n\), based on the weights from the previous step n-1.
w^{-T}(n-1): The weight at time n-1. It contains the filter coefficients or parameters learned up to the previous step.
x(n): The input_vector at time n.

Estimating the prior output signal, error signal, and filter weight samples is required when utilizing the RLS method. In the end, this leads to higher memory requirements.

B. Proposed Hybrid Audio Noise Cancellation Filter

In proposed filter the LMS and RLS adaptive filters are combined, to get the excellent results

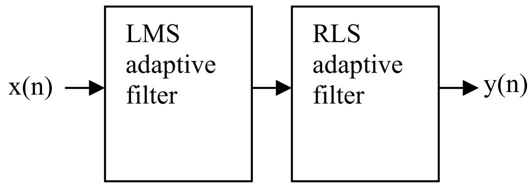

Fig. 2: Block Diagram of the Proposed System

This diagram in Figure 2 illustrates flow of proposed filter as the filter is made by combining logic of LMS and RLS so named as hybrid filter.

VI. IMPLEMENTATION

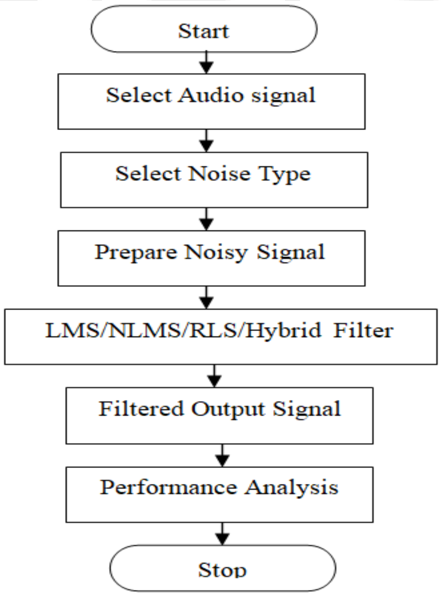

Fig. 3: Flow chart used for implementation

The proposed work was developed using MATLAB 2021, carefully implemented to fulfill both functional & non-functional criteria.

For experimentation three audio wave files are considered and for creating noisy audio signal four noise signals (AWGN, Johnson, random and uniform) are considered.

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A. LMS implementation output

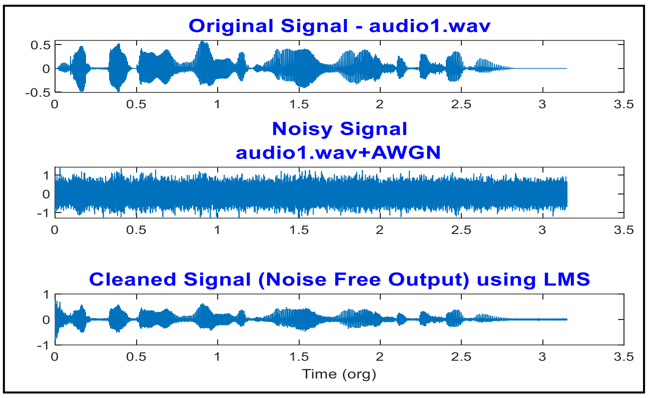

Fig. 4: LMS algorithm output for audio1+AWGN (a) audio1 (b) noisy signal with AWGN (c) filtered output signal.

In figure 4, top plot shows original Signal i.e. Clean Signal The middle plot shows how severely AWGN noise can affect a signal.

Bottom Plot shows Signal Cleaned by LMS.

Overall Interpretation tells that some minor distortion may still remain, but most noise is suppressed. LMS algorithm effectively recovers the signal to some extent.

B. NMS implementation output

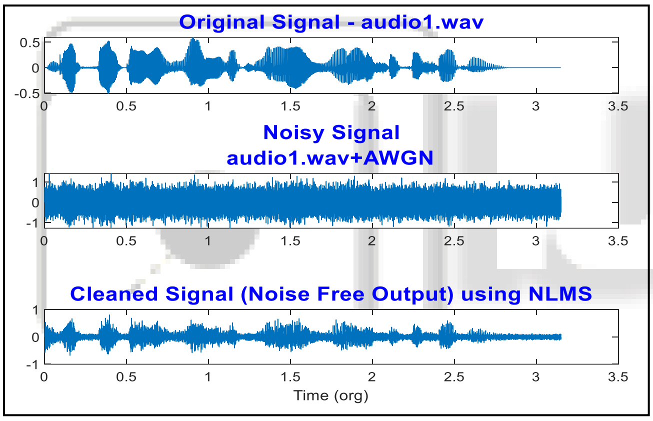

Fig. 5 NLMS algorithm output for audio1+AWGN (a) audio1 (b) noisy signal with AWGN (c) filtered output signal

From Figure 5 Interpretation made that the output signal has more distortion as compared to LMS. NLMS algorithm has less performance as compared to LMS.

C. RLS implementation output

From figure 6 we can interpret that the RLS algorithm is highly efficient for adaptive noise cancellation, making it suitable for applications like speech processing, audio enhancement, and communication systems where maintaining signal integrity is critical.

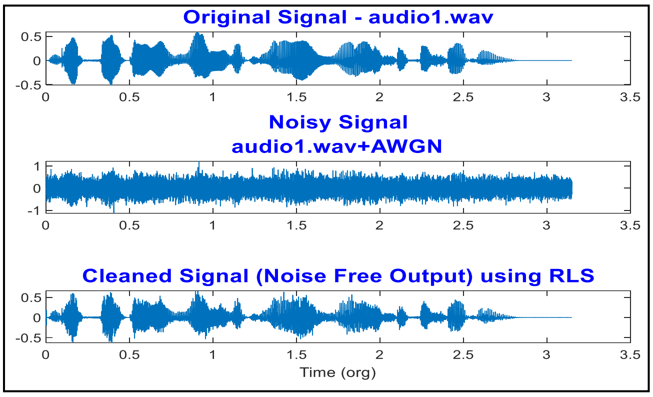

Fig. 6: RLS algorithm output for audio1+AWGN (a) audio1 (b) noisy signal with AWGN (c) filtered output signal.

D. Proposed Hybrid implementation

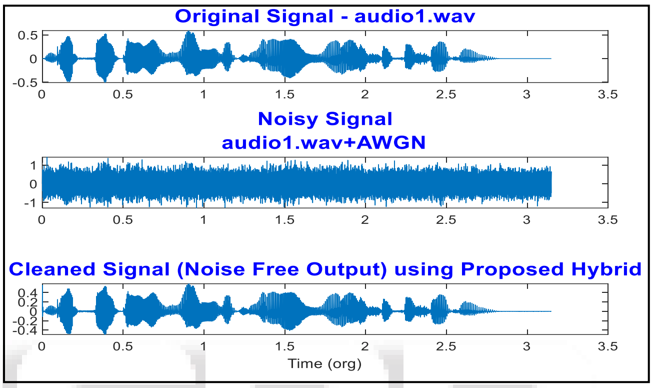

Fig. 7: Proposed Hybrid algorithm output for audio1+AWGN (a) audio1 (b) noisy signal with AWGN (c) filtered output signal.

As in figure 7, our proposed hybrid approach successfully reconstructs the original audio from a noisy environment, making it suitable for applications like speech enhancement, communication systems, and audio processing. It works far better that LMS or RLS.

VII. RESULT AND ANALYSIS

Following performance metrics are used to make comparisons of the proposed method with existing method.

A. Mean Squared Error (MSE) (Hodson et al., 2022)

MSE is computed by taking the average squared difference between a processed filtered signal and the original clean signal.

$$MSE = \frac{1}{N}\sum_{n=0}^{N-1}[x_{clean}[n] - x_{filtered}[n]]^2$$

A lower MSE indicates higher fidelity and less distortion.

B. Mean Absolute Error (MAE) (Hodson et al., 2022)

Calculated by dividing the total number of samples by the sum of absolute errors between the processed filtered signal and the original clean signal.

$$MAE = \frac{1}{N}\sum_{i=0}^{N-1}|\ y_i \ - x_i \ |$$

A lower MAE indicates good method.

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C. Signal to Noise Ratio (SNR) (Tobias May et al., 2018)

$$SNR_{dB} = 20 \; log_{10} \frac{V_{signal}}{V_{noise}}$$

Measured in decibels (dB) and represents the desired signal strength to background noise. Better, crisper audio quality is indicated by higher SNR.

Peak_Signal_to_Noise_Ratio (PSNR) (Kannadhasan Suriyan et al., 2022)

It shows that the reconstructed signal is of higher quality and closely resembles the original. A higher ratio denotes a stronger signal.

$$PSNR = 10 \; log_{10} \frac{MAX^2}{MSE}$$

D. Cross-correlation (CC)

Cross-correlation is a method in signal processing and statistics for assessing the similarity between two signals or time series by analyzing the displacement (lag) of one in relation to the other, with higher values indicating a stronger correlation.

E. Signal similarity accuracy

Signal similarity accuracy quantifies the resemblance between two signals on a scale from 0% to 100%. It is essential in signal processing, pattern recognition, and data analysis for comparing, aligning, or detecting signals, including applications in voice and image recognition.

1) Filtering Accuracy Comparison

Noise / Filter	AWGN
LMS	82.30 %
NLMS	28.50%
RLS	76.54%
Proposed Hybrid	99.37%

Table 1: Filtering Accuracy for Filters and Noises

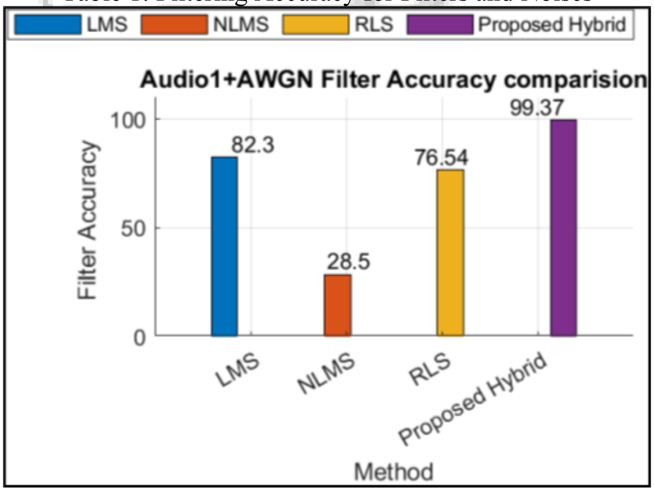

Fig. 8: Filter accuracy comparisons of audio1+AWGN

The graph in Figure 8 illustrates the accuracy of four adaptive filtering methods: LMS, NLMS, RLS, and a Proposed Hybrid method, applied to an audio signal affected by Additive White Gaussian Noise (AWGN). The Proposed Hybrid Method achieves the highest accuracy of 99.37%, demonstrating exceptional noise removal and superior filtering performance, likely due to the integration of multiple algorithms for enhanced convergence.

2) MSE comparison

Noise / Filter	AWGN
LMS	0.00091
NLMS	0.00137
RLS	0.00221
Proposed Hybrid	0.0001

Table 2: MSE for Filters and Noises

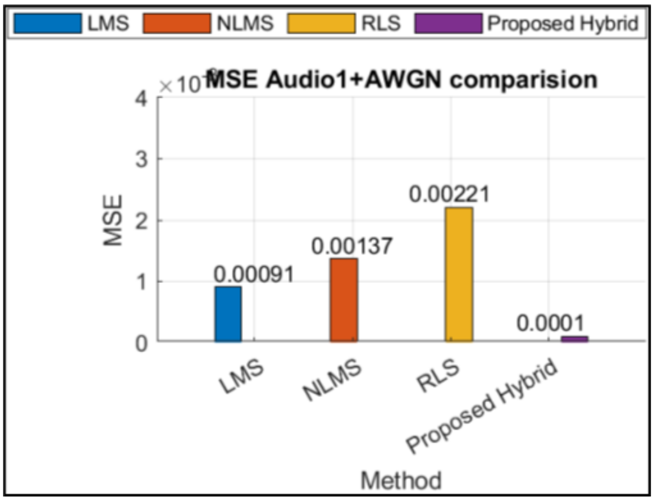

Fig. 9: MSE comparisons of audio1+AWGN

The MSE for various adaptive filtering methods applied to an audio signal affected by AWGN noise is depicted in figure 9. Among the methods LMS, NLMS, RLS, and the Proposed Hybrid algorithm, the Proposed Hybrid Method achieved the lowest MSE value of 0.00010, indicating superior noise removal efficiency. This suggests that the hybrid algorithm effectively combines the strengths of multiple adaptive techniques to enhance convergence and accuracy, proving to be significantly more accurate than the other filters for AWGN noise.

3) MAE Comparison

The graph in Figure 10 shows the performance of four adaptive filtering methods in terms of MAE when processing an audio signal corrupted by AWGN.

The Proposed Hybrid algorithm achieves the lowest MAE value of 0.00142. This indicates the best performance, as it minimizes the error between the original and filtered audio signals.

Noise / Filter	AWGN
LMS	0.01555
NLMS	0.06562
RLS	0.02739
Proposed Hybrid	0.00142

Table 3: MAE for Filters and Noises

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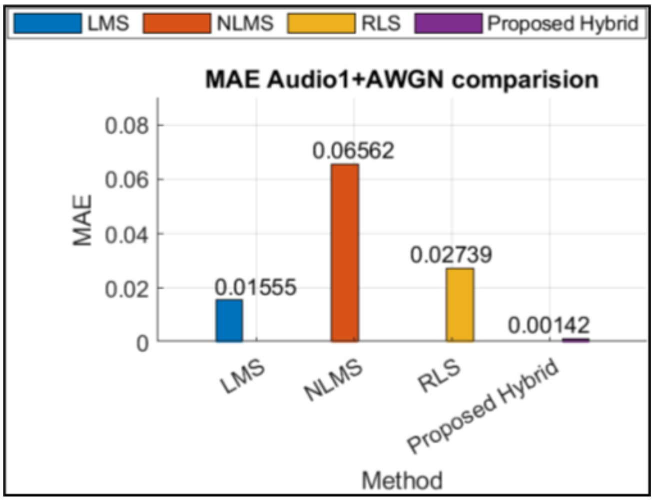

Fig. 10: MAE comparisons of audio1+AWGN

4) SNR Comparison

Noise / Filter	AWGN
LMS	23.34
NLMS	3.079
RLS	15.631
Proposed Hybrid	60.083

Table 4: SNR comparison for Filters and Noises

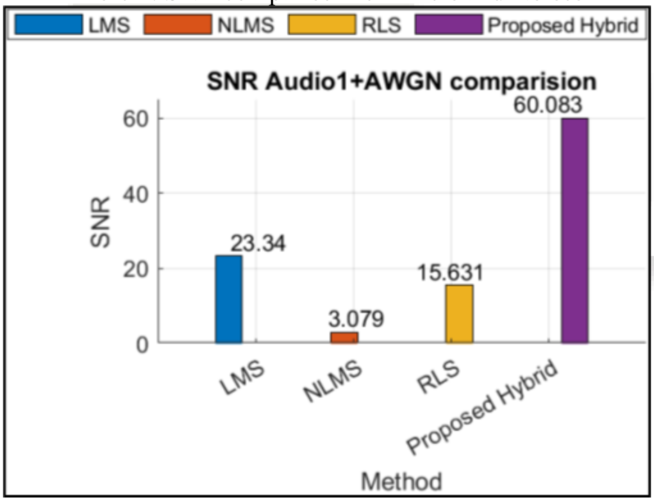

Fig. 11: SNR comparisons of audio1+AWGN

The graph in Figure 11 compares the SNR performance of four adaptive filtering methods LMS, NLMS, RLS, and the Proposed Hybrid method, when an audio signal is corrupted by AWGN. The Proposed Hybrid method significantly outperforms the other algorithms, demonstrating the highest signal quality post-filtering.

This indicates the best performance, as it minimizes the error between the original and filtered audio signals.

5) PSNR Comparison

Noise / Filter	AWGN
LMS	25.835
NLMS	15.705
RLS	21.981
Proposed Hybrid	44.207

Table 5: PSNR comparison for Filters and Noises

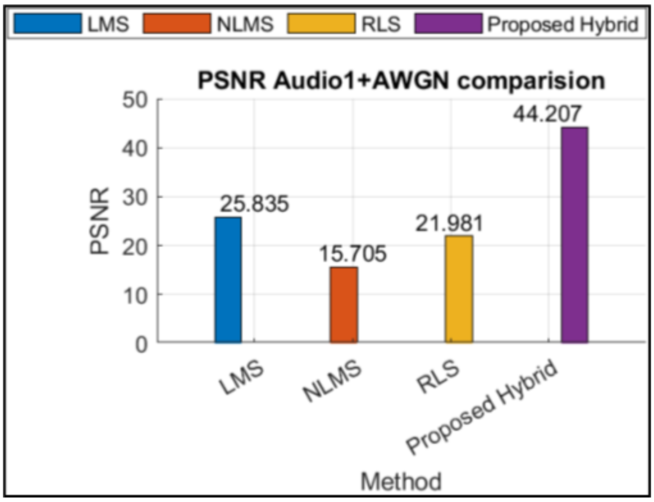

Fig. 12: PSNR comparisons of audio1+AWGN

When AWGN noise corrupts Audio1, Figure 12 displays the PSNR of several adaptive filtering techniques. PSNR values for LMS, NLMS, RLS and proposed hybrid methods are 25.835 dB, 15.705 dB, 21.981 dB, and 44.207 dB, respectively. The findings show that the suggested hybrid filtering method significantly enhances the audio signal's denoising capability.

6) Cross-Correlation (CC) Comparison

The bar chart in figure 13 compares the performance of adaptive filtering algorithms on CC Audio corrupted with AWGN noise. The proposed hybrid method achieves the highest score of 1.0, outperforming others and suggesting perfect correlation recovery. Higher bars represent better noise cancellation or signal restoration. The proposed hybrid excels, possibly by combining LMS and RLS strengths with novel enhancements,

Noise / Filter	AWGN
LMS	0.968
NLMS	0.668
RLS	0.926
Proposed Hybrid	1.000

Table 6: CC comparison for Filters and Noises

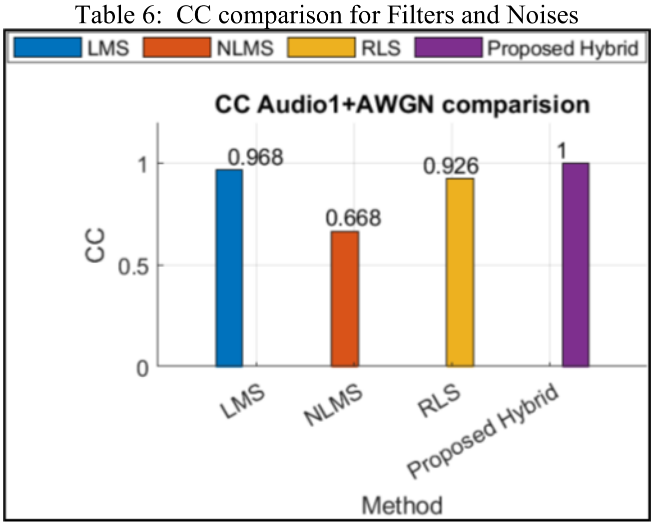

Fig. 13: CC comparisons of audio1+AWGN

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VIII. CONCLUSION

The proposed hybrid method demonstrates superior performance in audio signal processing compared to traditional filtering techniques (LMS, NLMS, RLS) across various metrics. It achieves the highest accuracy of 99.37%, the lowest MSE of 0.0001, and the lowest MAE of 0.00142. Additionally, it results in the highest SNR value of 60.083 and PSNR of 44.207, indicating significant noise reduction and clarity.

The proposed hybrid method also exhibits a perfect correlation coefficient (CC) of 1, outpacing LMS (0.968), NLMS (0.668), and RLS (0.926). Overall, the findings confirm that the proposed method is the most effective and reliable choice for enhancing audio signal quality in noisy environments.

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