IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 10, June 2026
Impact Factor: 8.2

Artificial Intelligence-Based Adaptive Filtering Techniques for Noise Reduction in Audio Electronics

Gaurav Ashok Bongale[1] and Dr. Shyam Sunder Kaushik[2]
[1]Research Scholar, [2]Professor
Department of Electronics and Telecommunications
Sunrise University, Alwar (Rajasthan)

Abstract: *Noise reduction is a fundamental requirement in modern audio electronics, particularly in speech communication, hearing devices, smart speakers, mobile devices, automotive infotainment systems, and digital recording equipment. Conventional fixed digital filters are effective when the spectral characteristics of interference are relatively stable, but their performance decreases when noise characteristics change over time. Adaptive filtering addresses this limitation by continuously modifying filter coefficients according to the observed signal and error. Classical algorithms such as Least Mean Square (LMS), Normalized Least Mean Square (NLMS), and Recursive Least Squares (RLS) provide an important foundation for adaptive noise cancellation.*

Recent developments increasingly combine adaptive filtering with artificial intelligence (AI), machine learning, optimization, and data-driven signal estimation to improve adaptation under non-stationary and complex acoustic conditions. Recent research demonstrates the continued relevance of LMS, NLMS, RLS, variable-step algorithms, and robust subband adaptive filtering for audio noise cancellation. This research paper proposes an AI-based adaptive filtering framework in which conventional adaptive filtering is enhanced through intelligent noise classification, dynamic parameter selection, and data-driven optimization.

Keywords: Artificial Intelligence, Adaptive Filtering, Audio Electronics, Noise Reduction, Machine Learning, Speech Enhancement, Signal-to-Noise Ratio.

I. INTRODUCTION

Audio electronics increasingly operates in environments containing multiple and dynamically changing sources of interference. Mobile communication devices, microphones, headphones, hearing systems, automotive audio equipment, conference systems, smart speakers, and digital recording platforms must process audio signals while simultaneously dealing with background speech, machinery, traffic, wind, electrical interference, reverberation, and acoustic echo. The principal objective of noise reduction is to suppress unwanted components while preserving the important temporal, spectral, and perceptual characteristics of the desired audio signal.

Traditional filtering techniques generally rely on predetermined frequency responses. Although low-pass, high-pass, band-pass, notch, FIR, and IIR filters remain valuable, a fixed filter cannot optimally respond to every changing acoustic environment. Adaptive filtering provides an alternative because its coefficients can change during operation. LMS and NLMS are widely used because of their relatively low computational requirements, while RLS generally provides faster convergence at increased computational cost.

The integration of artificial intelligence with adaptive filtering represents a further development. Instead of relying entirely on fixed step sizes, forgetting factors, filter orders, or manually selected operating modes, an intelligent controller can analyze signal characteristics and select or modify filter parameters dynamically. For example, an AI module can classify an incoming acoustic environment as speech-dominant, stationary-noise, impulsive-noise, or rapidly varying noise and subsequently select an appropriate adaptive filtering strategy.

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Recent research has explored robust RLS-based subband adaptive filtering for audio noise cancellation, demonstrating the importance of subband processing and robust loss functions when audio is contaminated by different noise distributions. Variable-step NLMS research has likewise demonstrated that changing the adaptation step according to signal conditions can improve the trade-off between convergence speed and steady-state error. Therefore, an AI-assisted adaptive framework can be designed to combine the computational efficiency of classical adaptive filters with the decision-making capabilities of machine learning.

Audio noise is inherently dynamic. Its amplitude, frequency distribution, statistical properties, and temporal characteristics may change within a short period. A fixed filter is therefore unable to maintain optimum performance across all operating conditions. Even conventional adaptive filters face a trade-off between rapid convergence and low steady-state error. A large adaptation step can improve convergence speed but may increase misadjustment, whereas a smaller step can improve steady-state behavior at the cost of slower adaptation. Similar limitations occur in RLS-based systems when computational complexity and numerical stability become important considerations.

The research problem is therefore to develop an intelligent adaptive filtering framework capable of identifying changing audio-noise conditions and dynamically selecting suitable filtering parameters or algorithms while maintaining low computational complexity and high audio quality.

II. ADAPTIVE FILTERING

An adaptive filter continuously updates its coefficients according to an error signal. For a desired signal (d(n)) and filter output (y(n)), the error is

$$e(n) = d(n) - y(n)$$

The filter coefficients are modified to minimize an objective function, commonly the mean-square error. Adaptive filters are particularly useful when the characteristics of the system or noise change over time.

LMS ALGORITHM

The LMS algorithm uses a gradient-descent approach. A simplified coefficient-update equation is

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

where (mu) represents the adaptation step size and x(n)) is the input vector. LMS is attractive for audio electronics because of its simplicity and low computational cost. However, its convergence behavior is affected by input-signal power and correlation.

NLMS ALGORITHM

NLMS normalizes the update according to the input-vector energy:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\epsilon + |\mathbf{x}(n)|^2} e(n)\mathbf{x}(n)$$

This normalization makes NLMS more robust to changes in signal amplitude. Research on acoustic echo cancellation has demonstrated the usefulness of NLMS and variable-step NLMS approaches in non-stationary environments.

RLS ALGORITHM

RLS minimizes a weighted sum of previous squared errors and uses a forgetting factor to emphasize recent observations. Its major advantage is rapid convergence, especially for correlated inputs, but it requires substantially greater computational resources than LMS and NLMS. Recent work has further investigated robust subband RLS methods for audio noise cancellation under Gaussian, impulse, and Poisson noise conditions.

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III. PROPOSED AI-BASED ADAPTIVE FILTERING FRAMEWORK

The proposed framework consists of five major stages:

Audio acquisition → Signal analysis → AI noise classification → Adaptive filter selection/parameter optimization → Enhanced audio output

The audio signal is first acquired through a microphone or audio interface. The signal is divided into suitable frames, after which spectral and temporal characteristics are extracted. Features may include short-time energy, zero-crossing rate, spectral centroid, spectral flatness, spectral entropy, estimated SNR, and frequency-band energy.

An AI classifier then determines the approximate noise condition. Based on this classification, an intelligent controller selects an adaptive filtering strategy. For relatively stationary noise, LMS or NLMS can be selected. For strongly correlated or rapidly changing interference, RLS or a robust subband adaptive filter can be activated. The AI controller may also dynamically adjust the step size, filter length, regularization parameter, or forgetting factor.

This hybrid design preserves the computational advantages of adaptive filtering while allowing intelligent adaptation to environmental conditions.

IV. PROPOSED EXPERIMENTAL DESIGN

A simulation-based experimental design can be used to evaluate the proposed system. Clean speech or music recordings can be combined with representative noise types such as white noise, babble noise, traffic noise, machinery noise, impulse noise, and environmental background noise. Several input SNR conditions can be generated to represent mild, moderate, and severe noise contamination.

The same noisy audio signals should be processed using LMS, NLMS, RLS, and the proposed AI-assisted adaptive filter. The output should then be evaluated quantitatively and perceptually.

Table 1. Proposed Experimental Dataset

Parameter	Proposed Setting
Audio content	Speech and music
Sampling frequency	16 kHz or 44.1 kHz
Noise categories	White, babble, traffic, machinery, impulse
Input SNR	−5, 0, 5, 10, 15 dB
Algorithms	LMS, NLMS, RLS, AI-assisted adaptive filter
Filter type	Adaptive FIR
Evaluation	SNR, MSE, NMSE, convergence time
Additional assessment	Perceptual audio quality
Experimental repetitions	Multiple trials for each condition

V. AI-BASED PARAMETER OPTIMIZATION

The AI component can be implemented using supervised learning, reinforcement learning, or an optimization-based controller. A supervised model can be trained using acoustic features as input and optimal filtering parameters as output. Alternatively, reinforcement learning can learn a policy that maximizes a reward based on noise suppression and audio preservation.

The objective function may be represented as

$$J = \alpha E_{\text{noise}} + \beta E_{\text{distortion}} + \gamma C$$

where (E_{noise}) represents residual noise, ($E_{distortion}$) represents distortion of the desired signal, (C) represents computational cost, and are weighting parameters.

This formulation allows the proposed system to balance noise reduction against audio fidelity and hardware limitations.

DOI: 10.48175/568

ISSN 2581-9429 IJARSCT

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Performance Evaluation Metrics

Table 2. Evaluation Metrics

Metric	Purpose	Desired Result
SNR	Measures signal quality relative to noise	Higher
SNR Improvement	Measures noise-reduction gain	Higher
MSE	Measures squared reconstruction error	Lower
NMSE	Normalized reconstruction error	Lower
Convergence Time	Measures adaptation speed	Lower
Computational Complexity	Measures processing requirements	Lower
Perceptual Quality	Evaluates listening quality	Higher
Residual Noise	Measures remaining interference	Lower

The principal metric should be SNR improvement:

$$\Delta SNR = SNR_{\text{out}} - SNR_{\text{in}}$$

A higher indicates stronger noise suppression, provided that the desired signal has not been excessively distorted.

VI. COMPARATIVE ANALYSIS OF ADAPTIVE FILTERING TECHNIQUES

Table 3. Comparison of Adaptive Filtering Algorithms

Algorithm	Convergence Speed	Computational Cost	Stability	Suitability
LMS	Moderate/Slow	Low	Good	Low-power audio systems
NLMS	Moderate/Fast	Low–Moderate	Good	General audio applications
RLS	Fast	High	Good with careful implementation	Rapidly changing systems
Variable-Step NLMS	Fast adaptive behavior	Moderate	Good	Non-stationary audio
Subband RLS	Fast	Moderate–High	Good	Colored audio/noise
AI-Assisted Adaptive Filter	Potentially adaptive	Moderate–High	Depends on controller	Complex dynamic environments

The literature indicates that LMS, NLMS, and RLS remain core adaptive-filtering methods, while variable-step and subband approaches address specific convergence and correlated-input problems.

VII. EXPECTED RESULTS

The proposed AI-assisted system is expected to outperform fixed-parameter adaptive filtering under highly variable noise conditions. LMS is expected to provide the lowest computational burden but slower adaptation under some correlated-input conditions. NLMS should offer a stronger balance between computational efficiency and robustness. RLS is expected to achieve faster convergence but at increased computational cost.

The AI-assisted approach is expected to achieve its principal advantage when noise conditions change rapidly. Instead of using one algorithm and one parameter configuration throughout the recording, the intelligent controller can modify the filtering strategy according to detected conditions.

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Table 4. Expected Performance Pattern

Method	Expected SNR Improvement	Expected MSE	Adaptation	Complexity
LMS	Moderate	Moderate	Moderate	Low
NLMS	High	Low–Moderate	Fast	Low–Moderate
RLS	High	Low	Very Fast	High
AI-assisted	Very High under variable noise	Low	Dynamic	Moderate–High

Note: Table 4 presents expected comparative behavior for a proposed research design rather than experimentally measured results.

VIII. APPLICATIONS IN AUDIO ELECTRONICS

AI-based adaptive filtering has significant potential in practical audio-electronic systems. In smartphones and wireless headsets, it can improve speech intelligibility in changing environments. In automotive systems, adaptive filters can suppress road, engine, and cabin noise. In hearing devices, intelligent filtering can differentiate speech from competing background sounds. Smart speakers can use adaptive filtering for acoustic echo cancellation and improved voice-command recognition.

Adaptive filtering is also important in conference systems because microphones may simultaneously receive direct speech, reflected sound, background noise, and loudspeaker output. Integrated adaptive echo and noise cancellation systems have previously combined adaptive filtering with additional spectral processing, demonstrating the practical importance of hybrid approaches.

IX. ADVANTAGES OF THE PROPOSED APPROACH

The principal advantage is adaptability. Traditional fixed filters cannot respond optimally to every acoustic environment, whereas an AI-assisted system can dynamically modify its filtering behavior. Additional advantages include improved handling of non-stationary noise, reduced manual parameter tuning, potential improvement in convergence speed, and the possibility of optimizing filtering according to both technical and perceptual criteria.

Robust subband adaptive-filter research further suggests that advanced adaptive structures can improve noise suppression for different noise distributions while maintaining theoretical convergence analysis.

Despite its potential, AI-based adaptive filtering introduces additional computational and implementation requirements. Training an AI model requires representative datasets covering diverse acoustic conditions. A model trained on limited noise categories may perform poorly in previously unseen environments. AI inference can also increase memory, processing, and power requirements, which is particularly important in battery-operated audio electronics.

Another challenge is the trade-off between aggressive noise suppression and preservation of speech or music characteristics. Excessive adaptation may remove useful signal components or introduce perceptual artifacts. Therefore, AI-based systems should optimize both noise reduction and audio fidelity rather than maximizing noise attenuation alone.

Future research can investigate lightweight neural networks, reinforcement-learning controllers, edge-AI implementations, and hardware-efficient adaptive filters for real-time audio devices. Hybrid time-domain/frequency-domain systems may further improve performance. Research can also investigate self-supervised learning for environments where labelled noise data are unavailable. Another promising direction is the integration of robust RLS, subband filtering, and AI-based parameter control. Recent research into physics-informed adaptive filtering also indicates a broader trend toward incorporating domain knowledge into adaptive learning systems.

X. CONCLUSION

Artificial Intelligence-Based Adaptive Filtering Techniques provide a promising approach for improving noise reduction in modern audio electronics. Classical LMS, NLMS, and RLS algorithms provide the mathematical and computational foundation for adaptive noise cancellation, while variable-step, subband, and robust filtering techniques address important limitations associated with convergence, correlated inputs, and impulsive noise.

The proposed AI-assisted framework extends these principles by introducing intelligent noise classification and dynamic parameter or algorithm selection. Such a system can respond more effectively to non-stationary acoustic environments than a fixed filtering configuration. Future experimental validation should compare the proposed method with conventional adaptive filters using standardized audio datasets and objective as well as perceptual quality measures. Overall, the integration of artificial intelligence with adaptive filtering represents an important research direction for intelligent microphones, headphones, communication devices, automotive audio systems, hearing technologies, and other real-time audio-electronic platforms.

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