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 4, July 2026

Impact Factor: 8.2

Review of Conventional and AI-Based Adaptive Filtering Techniques in Audio Systems

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: *Adaptive filtering is a fundamental technique for improving the quality of audio signals affected by environmental noise, acoustic echo, interference, reverberation, and changing acoustic conditions. Conventional adaptive algorithms such as Least Mean Squares (LMS), Normalized Least Mean Squares (NLMS), Recursive Least Squares (RLS), Affine Projection Algorithm (APA), and their variants have been extensively employed in active noise cancellation, acoustic echo cancellation, speech enhancement, hearing aids, teleconferencing, and communication systems. Their major advantages include low computational requirements, interpretability, stable real-time operation, and the ability to track slowly or moderately time-varying systems.*

Conventional methods can suffer from slow convergence, sensitivity to step-size selection, degradation under highly correlated inputs, and difficulty handling strongly nonlinear or rapidly changing acoustic environments. Recent developments in artificial intelligence have introduced neural-network-based adaptive filtering and hybrid DSP–AI architectures capable of learning complex temporal and spectral characteristics directly from data. Deep neural networks, recurrent neural networks, convolutional-recurrent networks, complex-valued networks, and full-band/sub-band architectures have demonstrated substantial improvements in speech enhancement and noise suppression. Reviews of recent research indicate a transition from purely model-based adaptive processing toward hybrid systems in which classical adaptive filters and AI models complement one another.

Keywords: Adaptive filtering, acoustic echo cancellation, noise cancellation, speech enhancement, artificial intelligence, deep learning, neural networks, audio processing.

I. INTRODUCTION

Audio systems operate in environments where the desired signal is frequently contaminated by unwanted acoustic components. Background conversations, traffic, machinery, wind, room reverberation, loudspeaker feedback, and electromagnetic or acoustic interference can significantly reduce speech intelligibility and perceived audio quality. Conventional fixed digital filters are effective when the spectral characteristics of the unwanted signal are approximately known and remain stable. However, real-world acoustic environments are time-varying, making it necessary for the filtering system to continuously adjust its parameters.

Adaptive filters address this problem by modifying filter coefficients according to the characteristics of the incoming signal and the error between desired and estimated signals. Adaptive filtering has therefore become an important technology in speech enhancement, active noise cancellation, acoustic echo cancellation, telecommunications, hearing devices, and hands-free communication systems.

These two equations describe the basic operation of an adaptive filter. The filter takes an input signal, processes it using adjustable filter coefficients, produces an output, and then compares that output with the desired signal to calculate the error. and the error is

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n)$$

The error signal is then used to update the filter coefficients. In the LMS algorithm, for example,

$$y(n) = w_0(n)x(n) + w_1(n)x(n-1) + w_2(n)x(n-2).$$

where (mu) represents the adaptation step size. The simplicity of this update rule explains why LMS remains one of the most widely used adaptive filtering methods.

Nevertheless, the requirements of modern audio systems have expanded considerably. Audio devices increasingly need to operate with non-stationary noise, multiple simultaneous speakers, nonlinear loudspeaker characteristics, changing acoustic paths, and strict computational and latency constraints. Recent investigations comparing LMS, NLMS, RLS, and APA show that there is no single conventional algorithm that simultaneously provides the best convergence, noise suppression, computational efficiency, and embedded feasibility. RLS can provide faster adaptation and strong tracking, whereas NLMS offers a useful balance between performance and complexity.

The rapid development of artificial intelligence has created another major direction in audio filtering. Deep neural networks can learn nonlinear mappings between noisy and clean audio representations. DNNs, CNNs, RNNs, LSTMs, complex-valued networks, and hybrid architectures have consequently become important approaches to speech enhancement and separation. A comprehensive review of DNN-based speech enhancement identifies applications including denoising, dereverberation, speaker extraction, and speaker separation.

The objective of this review is therefore to examine the evolution from conventional adaptive filtering toward AI-based and hybrid adaptive filtering systems and to compare their suitability for modern audio applications.

II. FUNDAMENTALS OF ADAPTIVE FILTERING IN AUDIO SYSTEMS

An adaptive filter is a digital filter whose coefficients are automatically adjusted according to a specified optimization criterion. Unlike a fixed filter, whose coefficients remain constant after design, an adaptive filter continuously responds to changes in the input signal and acoustic environment.

A typical audio adaptive filtering system contains four principal components:

1. **Reference input:** provides information about the interfering or desired acoustic signal.
2. **Adaptive filter:** estimates the unwanted component or system response.
3. **Error calculation:** determines the difference between the desired and estimated signals.
4. **Coefficient adaptation:** modifies filter coefficients to minimize an error criterion, usually mean-square error.
5. The most common optimization objective is

$$J(n) = E[e^2(n)]$$

where (J(n)) is the mean-square error and represents mathematical expectation.

In acoustic noise cancellation, the reference microphone captures a correlated noise signal, while a primary microphone receives the desired speech together with noise. The adaptive filter estimates the noise component, which is then subtracted from the primary signal. In acoustic echo cancellation, the reference is generally the far-end signal and the adaptive filter estimates the acoustic path between loudspeaker and microphone.

The choice of adaptive algorithm depends on convergence speed, computational complexity, numerical stability, steady-state error, tracking ability, and the statistical characteristics of the audio signal. These criteria remain central when selecting an algorithm for embedded audio systems.

III. CONVENTIONAL ADAPTIVE FILTERING TECHNIQUES

1. Least Mean Squares (LMS)

The LMS algorithm is one of the simplest adaptive filtering algorithms. It approximates the gradient-descent solution of the Wiener filtering problem without explicitly calculating the input correlation matrix. Its coefficient update is

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

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 4, July 2026

Impact Factor: 8.2

The major advantages of LMS are low computational complexity, straightforward implementation, and robustness. It is particularly suitable for real-time systems with limited processing resources. However, its convergence rate depends strongly on the eigenvalue spread of the input correlation matrix and on the selected step size. Consequently, highly correlated or colored audio inputs may result in relatively slow convergence.

2. Normalized LMS (NLMS)

NLMS modifies LMS by normalizing the adaptation step according to the instantaneous input signal energy:

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

Here, is a small positive constant used to prevent division by zero.

The normalization makes NLMS less sensitive to variations in input signal amplitude than conventional LMS. This is especially valuable for speech and audio signals whose energy can vary considerably over time. NLMS generally provides a good compromise between convergence, complexity, stability, and real-time implementation. Recent comparative work also identifies NLMS as an attractive compromise for resource-constrained audio systems.

3. Recursive Least Squares (RLS)

RLS minimizes a weighted sum of past squared errors rather than relying only on the instantaneous gradient. It therefore adapts rapidly, particularly when the input is highly correlated. RLS can achieve superior convergence and tracking performance compared with LMS-type algorithms, but this comes at the cost of substantially greater computational and memory requirements.

RLS has been investigated for acoustic noise cancellation and vehicle-noise suppression, where rapid adaptation is important. Its principal limitation for embedded applications is computational complexity and potential numerical instability.

4. Affine Projection Algorithm (APA)

APA extends the concept of NLMS by using multiple recent input vectors simultaneously. This can improve convergence for colored or correlated signals. The approach is particularly relevant to acoustic echo cancellation because speech signals contain significant temporal correlation.

Recent research notes that APA-type algorithms can converge faster than NLMS when dealing with correlated input signals, although their computational cost increases with the projection order.

5. Fast and Variable-Step Algorithms

The fixed step size used by LMS and NLMS creates a fundamental trade-off. A larger step size generally provides faster convergence but can increase steady-state error, while a smaller step size reduces misadjustment but slows adaptation. Variable-step and self-tuning algorithms have therefore been proposed to automatically modify the adaptation rate. Research on self-tuning adaptive filtering emphasizes that both step size and filter length substantially influence speech noise-cancellation performance.

VI. AI-BASED ADAPTIVE FILTERING TECHNIQUES

Artificial intelligence introduces a fundamentally different approach. Instead of relying entirely on an analytically derived coefficient-update equation, an AI model learns relationships between noisy and clean audio from training data.

A neural audio enhancement system can be represented as

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 4, July 2026
Impact Factor: 8.2

$$\hat{s}(t) = f_\theta(x(t))$$

where (x(t)) is the noisy input, f_θ is a neural network parameterized by and is the estimated clean signal.
The training process minimizes a loss function such as

$$L(\theta) = \frac{1}{N}\sum_{n=1}^{N} |s(n) - \hat{s}(n)|^2$$

although modern systems frequently employ spectral, perceptual, phase-aware, or multi-objective losses.

1. Deep Neural Networks

DNNs can learn nonlinear relationships between acoustic features and clean speech. They are useful when the relationship between interference and desired speech cannot be represented adequately by a linear adaptive filter. DNN-based approaches have been applied to denoising, dereverberation, and speech separation.

2. Recurrent Neural Networks

RNNs and LSTMs are particularly useful for audio because speech and music contain strong temporal dependencies. A recurrent model can use information from previous frames to determine the appropriate suppression or enhancement for the current frame.

RNNoise is an important example of a hybrid DSP/deep-learning approach. It uses a recurrent neural network to estimate information for noise suppression while retaining conventional signal-processing components. The design was explicitly aimed at achieving high-quality enhancement with sufficiently low complexity for real-time operation.

3. CNN and CRN Architectures

CNNs can identify local spectral patterns in spectrograms, while convolutional-recurrent networks combine spectral pattern extraction with temporal modeling. These architectures are particularly effective when audio is represented in the time-frequency domain.

4. Complex-Valued Neural Networks

Conventional magnitude-only enhancement can result in phase errors. Complex-valued networks attempt to estimate both real and imaginary components or otherwise model complex spectra. DCCRN, for example, combines complex-valued convolutional and recurrent operations for phase-aware speech enhancement. Its reported configuration used approximately 3.7 million parameters and achieved strong results in the INTERSPEECH 2020 Deep Noise Suppression challenge.

5. Full-Band and Sub-Band Neural Models

FullSubNet integrates full-band and sub-band processing. The full-band component captures global spectral relationships, while the sub-band component focuses on local frequency-specific patterns. This architecture demonstrates that global and local frequency information can complement each other in real-time speech enhancement.

V. HYBRID CONVENTIONAL–AI ADAPTIVE FILTERING

A particularly promising research direction is the combination of conventional adaptive filters and AI models. Rather than replacing classical adaptive filtering completely, AI can estimate parameters, detect acoustic conditions, predict masks, control adaptation rates, or compensate for nonlinearities.

Deep Adaptive Acoustic Echo Cancellation represents this concept by embedding a linear adaptive filtering algorithm as a differentiable layer within a DNN. The neural network can learn time-varying adaptation factors while the classical adaptive structure performs the actual adaptive filtering. This approach combines the interpretability and adaptability of classical filters with the learning capability of deep networks.

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 4, July 2026
Impact Factor: 8.2

Hybrid methods are attractive because conventional filters generally have predictable computational requirements and low latency, while neural networks can address nonlinear acoustic phenomena that are difficult for linear adaptive algorithms. The hybrid DSP/deep-learning philosophy has already demonstrated practical feasibility in real-time speech enhancement.

VI. COMPARATIVE REVIEW OF CONVENTIONAL AND AI-BASED TECHNIQUES

Table 1. Comparison of Conventional and AI-Based Adaptive Filtering Techniques

Technique	Basic Principle	Convergence/Adaptation	Computational Complexity	Noise Suppression	Main Advantages	Main Limitations	Typical Applications
LMS	Gradient-descent coefficient update	Slow to moderate	Low	Moderate	Simple, robust, inexpensive	Step-size sensitivity; slow with correlated inputs	ANC, basic speech enhancement
NLMS	LMS normalized by input energy	Moderate to fast	Low–moderate	Good	Stable under varying signal levels; practical	Still limited for highly correlated/nonlinear environments	ANC, AEC, hearing devices
RLS	Recursive least-squares optimization	Very fast	High	Very good	Rapid tracking and convergence	High computational cost; numerical issues	AEC, rapidly changing environments
APA	Uses multiple recent input vectors	Fast for correlated signals	Moderate–high	Very good	Better convergence for colored input	Higher complexity than NLMS	AEC, speech enhancement
Variable-step LMS/NLMS	Adaptation step changes according to signal/error	Adaptive	Low–moderate	Good	Balances convergence and steady-state error	Parameter/control design required	Real-time noise cancellation
DNN	Learns nonlinear noisy-to-clean mapping	Data-dependent	Moderate–very high	Very good	Nonlinear modeling capability	Training data and computational resources required	Speech enhancement

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 4, July 2026

Impact Factor: 8.2

RNN/LSTM	Learns temporal dependencies	Strong temporal adaptation	Moderate–high	Very good	Handles time-varying speech/noise	Inference latency and training complexity	Real-time speech enhancement
CNN/CRN	Learns local spectral and temporal features	Data-dependent	Moderate–high	Very good	Strong time-frequency representation	Model size and latency	Speech denoising
DCCRN	Complex-valued neural processing	Data-driven	Moderate–high	Excellent	Phase-aware enhancement	Training and implementation complexity	Speech enhancement
FullSub Net	Full-band + sub-band neural modeling	Data-driven	Moderate–high	Excellent	Combines global and local spectral information	Requires training data and model optimization	Real-time speech enhancement
Hybrid DSP–AI	Classical adaptive filtering + neural learning	Fast/adaptive	Moderate–high	Excellent	Combines interpretability, low latency, and nonlinear learning	Architecture and training complexity	AEC, ANC, communication systems

*Note: The comparison is qualitative because performance depends strongly on filter order, acoustic environment, training data, hardware, latency constraints, and evaluation protocol. Findings concerning LMS/NLMS/RLS/APA trade-offs are consistent with comparative and review literature. *

VII. COMPARATIVE PERFORMANCE CRITERIA

Several parameters should be considered when comparing adaptive filtering techniques.

1. Convergence Speed

Convergence speed describes how rapidly the adaptive filter approaches an appropriate solution after an environmental change. LMS generally converges more slowly than RLS, while NLMS improves robustness to changes in input power. APA can provide faster convergence than NLMS for correlated input signals.

2. Steady-State Error

Steady-state error measures the residual error after adaptation has stabilized. Smaller error generally corresponds to better noise cancellation, although minimizing mathematical error alone does not guarantee better perceived audio quality.

DOI: 10.48175/568

ISSN 2581-9429 IJARSCT

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 4, July 2026
Impact Factor: 8.2

3. Computational Complexity

Computational complexity is particularly important in mobile phones, hearing aids, wireless earbuds, embedded DSP processors, and IoT audio devices. LMS and NLMS are attractive because of their relatively low computational requirements, whereas RLS and large neural networks require more resources.

4. Tracking Ability

Tracking ability determines how well the algorithm follows changes in the acoustic environment. RLS and more advanced adaptive algorithms generally provide strong tracking, whereas simple LMS can be slower when the acoustic path changes rapidly.

5. Perceptual Audio Quality

Traditional objective metrics such as MSE and SNR do not always correlate perfectly with human perception. AI-based enhancement has therefore increasingly used perceptual and intelligibility-oriented evaluation. Neural approaches can produce improved perceptual quality, although they can also introduce speech distortion or artifacts when the training distribution differs substantially from the real environment.

VIII. APPLICATIONS IN AUDIO SYSTEMS

1. Active Noise Cancellation

Adaptive filtering is central to ANC headphones and other active noise-control devices. LMS and FxLMS-type methods can estimate the acoustic path and generate anti-noise signals. AI can improve ANC by predicting environmental noise characteristics and controlling adaptation.

2. Acoustic Echo Cancellation

AEC is widely used in smartphones, smart speakers, video-conferencing systems, and VoIP. The adaptive filter estimates the acoustic path between loudspeaker and microphone. Double-talk and nonlinear loudspeaker behavior remain major challenges. APA, RLS variants, and hybrid AI methods are therefore important research directions.

3. Speech Enhancement

Speech enhancement aims to improve speech intelligibility and quality in noisy environments. Conventional adaptive filters remain useful when a suitable noise reference is available, while AI methods are advantageous for complex, non-stationary, and poorly modeled interference.

4. Hearing Aids

Hearing devices require low-latency processing and low power consumption. NLMS and related adaptive methods are attractive because of their efficiency, while lightweight neural networks offer opportunities for improved personalized noise suppression.

5. Teleconferencing and VoIP

Modern communication platforms require simultaneous echo cancellation, noise suppression, dereverberation, and speech enhancement. Hybrid filtering is particularly appropriate because classical DSP can satisfy strict latency requirements while AI models can address difficult nonlinear acoustic conditions.

6. Automotive Audio

Vehicles contain rapidly changing noise sources including engines, tires, wind, and road surfaces. Adaptive filtering has been applied to vehicle noise suppression, and comparative research has evaluated LMS, NLMS, RLS, and QR-RLS under automotive conditions.

IX. ADVANTAGES AND LIMITATIONS

Table 2. Major Advantages and Limitations

Category	Advantages	Limitations
LMS	Very simple; low cost; easy hardware implementation	Slow convergence in correlated environments
NLMS	Better normalization; robust to signal-level variation	Additional division operation; limited nonlinear modeling

RLS	Rapid convergence; strong tracking	High complexity and memory requirements
APA	Effective with correlated signals	Complexity increases with projection order
AI/DNN	Learns complex nonlinear relationships	Requires training data and computational resources
RNN/LSTM	Excellent temporal modeling	Potential latency and recurrent computation
CNN/CRN	Strong spectral feature extraction	Model optimization required for embedded systems
Complex neural networks	Can model magnitude and phase jointly	Greater implementation and training complexity
Hybrid DSP–AI	Combines classical and learning-based strengths	More complicated system design and validation

X. CONCLUSION

Conventional and AI-based adaptive filtering represent two complementary stages in the development of modern audio enhancement technology. LMS remains attractive because of its simplicity and low computational complexity, while NLMS provides improved robustness to varying signal power and is particularly suitable for real-time systems. RLS provides faster convergence and strong tracking but requires substantially greater computational resources. APA improves adaptation for correlated signals but increases complexity. These conventional algorithms remain highly relevant because they are interpretable, computationally efficient, and well suited to embedded applications.

AI-based methods have expanded the capabilities of audio filtering by learning nonlinear spectral and temporal relationships from data. DNNs, RNNs, CNN/CRN architectures, DCCRN, and FullSubNet demonstrate how data-driven models can address complex noise and speech-enhancement problems.

However, AI should not necessarily be viewed as a complete replacement for conventional adaptive filtering. Hybrid DSP–AI approaches offer a more balanced pathway by combining low-latency signal-processing structures with the nonlinear modeling capability of neural networks. Deep adaptive AEC and hybrid DSP/deep-learning speech enhancement provide evidence for this direction.

Overall, the most promising future architecture for intelligent audio systems is likely to be an adaptive hybrid system capable of selecting or controlling filtering strategies according to acoustic conditions. Such systems can potentially achieve high noise suppression, low speech distortion, rapid environmental tracking, low latency, and efficient hardware utilization. The continued integration of adaptive signal processing, machine learning, and edge computing is therefore expected to play a central role in the development of next-generation audio systems.

REFERENCES

1. Abhishek, R., & Ramesh, V. (2015). Acoustic noise cancellation by NLMS and RLS algorithms of adaptive filter. *International Journal of Science and Research, 4*(5), 198–202.
2. Chandrashekar, H. M. (2018). A review of adaptive algorithms for acoustic echo cancellation. *International Journal of Engineering Research & Technology*.
3. Dewasthale, M., & Kharadkar, R. D. (2017). High performance self tuning adaptive filter algorithm for noise cancellation in speech. *Journal of Intelligent & Fuzzy Systems, 32*(4).
4. Hadei, S. A., & Lotfizad, M. (2011). A family of adaptive filter algorithms in noise cancellation for speech enhancement. *arXiv*.
5. Hao, X., Su, X., Horaud, R., & Li, X. (2021). FullSubNet: A full-band and sub-band fusion model for real-time single-channel speech enhancement. *Proceedings of ICASSP 2021*, 6633–6637.
6. Hu, Y., Liu, Y., Lv, S., Xing, M., Zhang, S., Fu, Y., Wu, J., Zhang, B., & Xie, L. (2020). DCCRN: Deep complex convolution recurrent network for phase-aware speech enhancement. *Interspeech 2020*.

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 4, July 2026

Impact Factor: 8.2

7. Martinek, R., Kahankova, R., Nedoma, J., Fajkus, M., Skacel, M., & others. (2018). Comparison of the LMS, NLMS, RLS, and QR-RLS algorithms for vehicle noise suppression. *Proceedings of the 10th International Conference on Computer Modeling and Simulation*, 23–27.
8. Nagal, R., Kumar, P., & Bansal, P. (2017). A survey with emphasis on adaptive filter structure, LMS and NLMS adaptive algorithm for adaptive noise cancellation system. *Journal of Engineering Science and Technology Review, 10*(2), 150–160.
9. Ochieng, P. (2023). Deep neural network techniques for monaural speech enhancement and separation: State of the art analysis. *Artificial Intelligence Review, 56*, 3651–3703.
10. Prasath, C. A. (2025). Adaptive filtering techniques for real-time audio signal enhancement in noisy environments. *National Journal of Signal and Image Processing, 1*(1), 26–33.
11. Valin, J.-M. (2018). A hybrid DSP/deep learning approach to real-time full-band speech enhancement. *Proceedings of the IEEE Multimedia Signal Processing Workshop*.
12. Wang, Z.-Q., Wang, P., & Wang, D. (2020). Complex spectral mapping for single- and multi-channel speech enhancement and robust ASR. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 28*, 1778–1787.
13. Zhang, H., Kandadai, S., Rao, H., Kim, M., Pruthi, T., & Kristjansson, T. (2022). Deep adaptive AEC: Hybrid of deep learning and adaptive acoustic echo cancellation.

DOI: 10.48175/568