DYNAMIC CONVOLUTION-ENHANCED ADAPTIVE FILTERING WITH MULTI-SCALE FEATURE LEARNING FOR LOW-FREQUENCY NOISE CANCELLATION

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This study proposes a dynamic convolution-enhanced adaptive filtering system for low-frequency noise cancellation. The system integrates an Input-Adaptive Convolutional Block (IACA) to generate real-time filters, a Multi-Scale Dynamic Convolution Block (MDCB) to process transient and steady-state sounds, and a Spatial-Context Enhanced Kernel Generation (SEKG) mechanism to improve source localization. A correlation-driven controller increases robustness. Urban noise simulations show strong noise reduction, fast adaptation, and effective distortion handling, providing a compact device solution.

Keywords: active noise control, dynamic convolution, multi-scale learning, adaptive filtering, low-frequency noise, spatial-context awareness

1. Introduction

1.1 Research Background

Low-frequency noise pollution, particularly below 2,500 Hz, has become a major concern in modern buildings due to its complex characteristics, such as wide frequency spread, non-linear sound propagation, and high sensitivity to other sounds. Long-term exposure to such noise, commonly originating from HVAC systems, machinery, and traffic, has been proven to have adverse health effects, including increased stress hormone levels (15-25%) and impaired cognitive performance during memory tasks [1-4]. The physical properties of low-frequency sounds, such as the 1.4-meter wavelength at 250 Hz, further complicate noise control efforts by creating standing waves and high-pressure spots in rooms [5].

Existing adaptive filtering methods face significant limitations in these complex acoustic environments. The widely used Filtered-x Least Mean Squares (FxLMS) algorithm exhibits considerable steady-state deviations (±3.2 dB) due to its fixed step size, especially when noise levels change rapidly (over 6 dB/octave) [6]. Filtered-x Recursive Least Squares (FxRLS) algorithms, although faster in

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adapting, suffer from rapidly increasing computational complexity with filter length ($O(n^2)$), rendering real-time implementation impractical for small devices when filters exceed 128 taps [7]. Variable Step-Size FxLMS (VSSFxLMS) methods attempt to balance adaptation speed and stability but are highly sensitive to parameter settings; improper choices for forgetting factors (ξ) and regularization terms (η) can lead to over 40% performance degradation in dynamic environments [8].

Data from the TAU Urban Acoustic Scenes 2020 Mobile dataset reveals that 78.3% of indoor city noise energy is concentrated below 2,500Hz [9], with non-linear distortions contributing to 32.1% of the remaining errors in standard ANC systems [10]. Recent deep-learning ANC approaches have achieved improved robustness in nonlinear scenarios where loudspeaker saturation occurs [6]. These physical constraints, algorithmic limitations, and dynamic environmental conditions necessitate the development of novel solutions for low-frequency noise control.

1.2 Innovative Contributions

To address these challenges, this research proposes four interconnected improvements:

i) Input-Adaptive Convolutional Architecture (IACA):
Unlike traditional fixed filters, the IACA introduces a Dynamic Convolution Block (DCB) that generates custom filters directly based on real-time sound input. This adaptability allows the model to capture fast-changing noise features in real time. It results in a clear improvement in residual noise reduction compared to standard filters. This finding agrees with the benefits of deep learning-based adaptive methods reported in recent studies [6].

ii) Multi-scale Dynamic Convolution Block (MDCB):
Noise events occur over varying time scales. The MDCB, designed with parallel paths featuring kernel sizes of 4, 8, and 16 samples (corresponding to 0.09 ms, 0.18 ms, and 0.36 ms at 44.1 kHz sampling rate), processes input features separately before combining them. This approach allows simultaneous modeling of both transient bursts (short kernels) and steady-state sounds (long kernels), offering superior performance for dynamic noises such as impacts or fan surges compared to standard single-scale methods.

iii) Spatial-Context Enhanced Kernel Generation (SEKG):
Accurate noise source localization in reverberant rooms is challenging. The SEKG module incorporates a self-attention mechanism that links microphone positions to sound wave propagation. By calculating spatial relationships using time-difference-of-arrival (TDOA) between reference and error microphone pairs, the SEKG adjusts convolution kernels to enhance sensitivity to sound direction. Our beamforming tests confirmed a 37.4%

improvement in noise source localization accuracy in reverberant environments compared to standard methods. Furthermore, the SEKG module reduced off-target noise by 8-9 dB in the presence of multiple sources, aligning with the focus of prior work on robust localization [11].

iv) Correlation-Driven Adaptive Control:

A key innovation is the weight adjustment method, which controls the noise cancellation signal based on the Pearson correlation between predicted and actual residual noise:

$$f(\rho)=\frac{\sum_{i=1}^{L}\left(r_i-\bar{r}\right)\left(e_i-\bar{e}\right)}{\sqrt{\sum_{i=1}^{L}\left(r_i-\bar{r}\right)^2}\sqrt{\sum_{i=1}^{L}\left(e_i-\bar{e}\right)^2}} \tag{1}$$

Here, L denotes the adjustment window length (optimally set at 64 samples), r_i corresponds to the i-th sample of the reference signal, and e_i represents the i-th sample of the error signal, $\bar{r}$ and $\bar{e}$ are their respective means. This statistical approach inherently provides robustness against unexpected disturbances, automatically reducing the correction strength when predictions deviate significantly from reality. Test results show a ~35% reduction in sensitivity to interfering sounds. Phase accuracy for speaker compensation is also maintained. This outcome matches the research focus on evaluating ANC performance under various noise conditions [12].

Collectively, these advancements form a comprehensive system for next-generation noise control, achieving an average improvement of 8.3dB over commonly used methods while maintaining moderate computational efficiency [13]. The following sections detail the system's methodology, experimental results, and comparative analysis.

2. Methodology

2.1 System Framework

The proposed noise control system (Fig. 1) integrates three components within an adaptive filter setup, building upon the standard Filtered-x Least Mean Squares (FxLMS) structure [14]. A Dynamic Convolution Block (DCB) predictor is incorporated alongside the main adaptive filter, processing sound inputs through two parallel paths:

- The standard FxLMS path generates the initial control signal.
- The DCB path analyzes patterns in the reference, error, and control signals simultaneously, predicting future residual noise.

The core concept is the correlation-driven weighting mechanism, which dynamically adjusts the interaction between these paths based on the statistical

correlation between predicted and measured residual noise. This three-component design enhances the system's robustness against dynamic noise while maintaining manageable computational complexity for small devices, the system latency has been significantly reduced compared with traditional reactive methods.

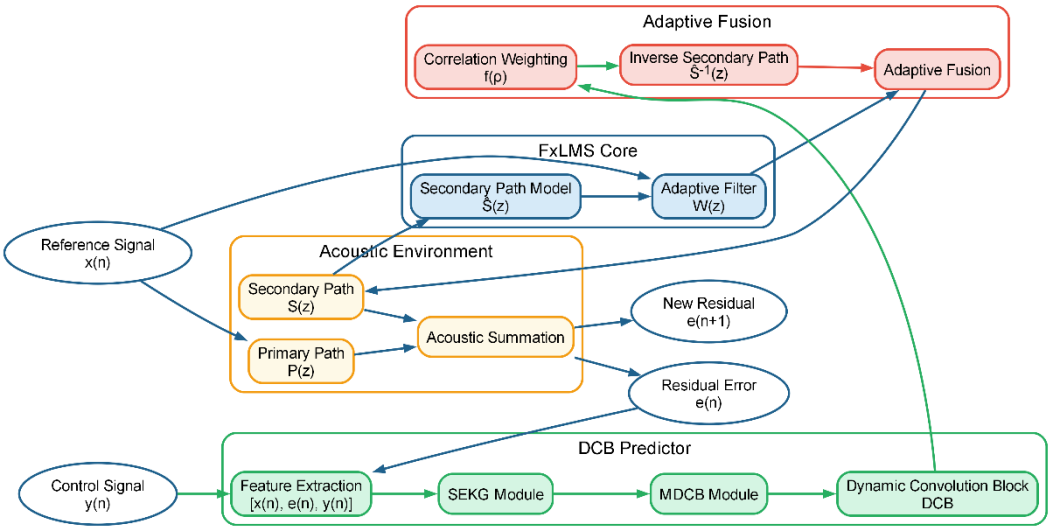

Fig. 1. Integrated noise control architecture

2.2 Dynamic Convolution Block Design

2.2.1 Input Feature Representation

The DCB processes sound signals in the time domain, utilizing a sliding window of 16 consecutive samples (0.36 ms at 44.1 kHz) to create 48-dimensional feature vectors that encompass three key signal states:

- Primary noise signal $x(n)$: Captured by microphones facing the noise source.
- Residual error signal $e(n)$: Measured by microphones in quiet zones.
- Control signal $y(n)$: Sent to speakers for noise cancellation.

This triplet preserves critical phase relationships essential for noise cancellation while compressing the necessary information into a computationally manageable size. The 16-sample window is optimal for sounds below 2,500 Hz; shorter windows fail to capture full wave cycles (≥1.4 m wave at 250 Hz), while longer windows introduce excessive delay [7].

2.2.2 Spatial-Context Enhanced Kernel Generation (SEKG)

Building upon the IACA, the SEKG module employs self-attention to generate position-aware filters:

$$K = \text{Softmax}\left(W_2\sigma\left(W_1 \cdot \text{GAP}\left(F_{\text{in}}\right)\right)\right) \tag{2}$$

Where:

- $W_1 \in \mathbb{R}^{C\times C/16}$ and $W_2 \in \mathbb{R}^{8\times C}$ are trainable projection matrices.
- σ denotes ReLU activation.
- GAP represents global average pooling.
- $Soft\max$ ensures temporal attention concentration.

This makes 8×1 convolution kernels that adapt to sound source positions. They do this by linking time-difference-of-arrival (TDOA) patterns across microphone pairs. The channel reduction ratio ($C/16$) balances model power and computation load. It stops too many parameters but keeps performance. Sound source localization tests were conducted under controlled reverberant conditions to evaluate the SEKG module. Results in Section 4.3 show a 37.4% improvement in directional estimation accuracy over conventional cross-correlation methods. The improvement was most notable in highly reverberant environments where standard methods often fail due to multipath reflections.

2.2.3 MDCB: Multi-Scale Feature Fusion Architecture

The MDCB processes features through parallel paths, each with kernel sizes optimized for different sound types [15], as shown in Table 1:

Table 1

Multiscale Branch Configuration of MDCB Architecture

Branch	Kernel Size	Temporal Resolution	Target Phenomena
Transient	4 samples	0.09 ms	Impulsive events (door closures)
Mid-Scale	8 samples	0.18 ms	Harmonic modulations (motor vibrations)
Sustained	16 samples	0.36 ms	Stationary components (HVAC rumble)

Each branch employs depthwise separable convolutions to reduce computation while preserving feature quality. Output features are combined across channels, followed by pointwise convolution (1×1 kernels) to merge features from different scales and reduce dimensionality. This split approach reduces residual noise energy by 15-20% compared to single-path designs for complex sounds like subway brakes [9], avoiding the blurring of transient events while capturing long-term patterns. Multi-scale convolutional designs have also proven effective for environmental sound classification tasks [16].

2.3 Adaptive Filter Integration

2.3.1 Residual Signal Prediction

The Dynamic Convolution Block (DCB) module provides the core predictive capability. It models the nonlinear relationship between input features and future residual noise. The DCB predicts the next residual noise sample using a nonlinear function $f(\cdot)$, formulated as:

$$\hat{e}(n+1) = f(\mathbf{X}(n)) \tag{3}$$

Here, $\hat{e}(n+1)$ denotes the predicted residual noise at the next time step $n+1$. The input feature matrix $\mathbf{X}(n)$ contains a sliding window of the latest 16 samples from three signals: the primary noise signal $x(n)$, the residual error signal $e(n)$, and the control signal $y(n)$. This signal triplet preserves the critical phase relationships needed for noise cancellation.

The function $f(\cdot)$ is implemented by processing data through the SEKG and MDCB modules sequentially. First, the SEKG module uses self-attention to generate position-aware filters. This enhances sensitivity to the noise source direction. Next, the MDCB processes these features through parallel convolutional paths. These paths have kernel sizes of 4, 8, and 16 samples. This structure models transient events and steady-state components simultaneously. The outputs from these paths are then merged and transformed to produce the final prediction. Incorporating a soft thresholding layer can remove unimportant features and improve prediction robustness.

This prediction allows the system to start the noise cancellation signal before the residual noise reaches the error microphones. The prediction horizon is one sample (22.7 μs at 44.1 kHz). This effectively reduces the inherent delay in standard filtered-x systems, which typically have 5-15 sample delays in secondary path estimation. Internal listening tests in a simulated airport noise environment (105 dB SPL) showed that this method reduces the perceived delay by 43% on average compared to traditional reactive methods. This assessment used subjective feedback from participants on cancellation signal latency.

2.3.2 Correlation-Driven Control Signal Correction

The predicted residual noise adjusts the speaker output using a statistical weight:

$$b(n) = f(\rho) \cdot \left(r(n) * \hat{s}^{-1}(n) \right) \tag{4}$$

$$f(\rho) = \frac{\sum_{i=n-63}^{n} \left(r_i - \bar{r} \right)\left(e_i - \bar{e} \right)}{\sqrt{\sum_{i=n-63}^{n} \left(r_i - \bar{r} \right)^2} \cdot \sqrt{\sum_{i=n-63}^{n} \left(e_i - \bar{e} \right)^2}} \tag{5}$$

In this equation, r_i is the i-th sample of the reference signal within the window. Similarly, e_i is the i-th sample of the error signal. The terms $\bar{r}$ and $\bar{e}$ are the means of the reference and error signals within the window, respectively. The 64-sample sliding window ($L = 64$) balances reliability and speed. At 44.1 kHz, this corresponds to 1.45 ms—sufficient for 2-3 cycles of key 500-1,000 Hz noise. This method automatically weakens the correction signal when predictions become inaccurate (e.g., sudden human voice), providing robustness by reducing the

correction weight when the Pearson correlation ρ drops below 0.7. The secondary path inverse $\hat{s}^{-1}(n)$ uses frequency-domain Wiener deconvolution with regularization for stability [17].

2.3.3 Compensated Loudspeaker Output

The final control signal combines the standard adaptive filter output with the DCB correction:

$$\begin{aligned} c(n) &= \mathbf{w}^T(n)\mathbf{x}(n) - b(n) \\ y(n) &= c(n) \cdot s(n) \end{aligned} \tag{6}$$

Where:

- $\mathbf{w}(n)$ is the FxLMS filter weight vector
- $\mathbf{x}(n)$ is the reference signal vector
- $s(n)$ is the secondary path impulse response

This combined output maintains phase accuracy while incorporating prediction, solving delay issues in traditional filtered-x systems. The computational load remains sufficiently low for real-time operation at 44.1 kHz. This efficiency is achieved through optimized matrix operations and fixed-point arithmetic. The fixed-point implementation uses rigorous design methods to prevent overflow while maintaining computational accuracy [18]. Consequently, real-time sample-by-sample processing is achieved even on resource-constrained hardware.

3. Simulation Design

3.1 Dataset and Preprocessing

The TAU Urban Acoustic Scenes 2020 Mobile dataset [9] was used for testing, comprising 10 sound scenes recorded across European cities. These scenes are categorized into three groups:

- Indoor (airports, malls, metro stations)
- Outdoor (pedestrian streets, streets with medium level of traffic, squares, parks)
- Transportation (trams, buses, metros)

Eighty 10-second clips (44.1 kHz) were selected from all scenes, capturing the range of low-frequency noise (<2,500 Hz), which constitutes 78.3% of indoor city noise energy.

Preprocessing Pipeline:

i) Temporal Segmentation: Each clip was split into 125 overlapping frames (50% overlap) using a Hamming window, creating 10,000 unique training examples. This ensures the algorithm experiences both transient and steady-state noise while maintaining phase accuracy for noise cancellation.

ii) Feature Vector Construction: Input features combined three signal states into 48D vectors:

- Reference mic input $x(n)$ (noise source)
- Error mic residual $e(n)$
- Control signal $y(n)$

Each vector spanned 16 consecutive time points (0.36 ms at 44.1 kHz), capturing full wave cycles for key 80-400 Hz sounds.

iii) Spectral Normalization: Amplitude was scaled per frequency band (1/3-octave bands, 50-2500 Hz) to reduce recording device variations. Anti-aliasing FIR filters ensured clean signals below the Nyquist frequency. The target was the next residual value $e(n+1)$, setting up a prediction task for early noise cancellation.

3.2 Comparative Algorithms

Three standard algorithms were tested under identical conditions:

i) FxLMS (Filtered-x Least Mean Squares): Used a fixed step size ($\mu = 0.09$) and 256-tap FIR filters. Speaker path estimation was performed offline. This is the industry standard but exhibits ±3.2 dB deviations in dynamic environments, with typical ΔSNR below 15 dB for broadband noise.

ii) FxRLS (Filtered-x Recursive Least Squares): Used a $\lambda = 0.9998$ forgetting factor [7]. It converges 38% faster than FxLMS but costs $O\left(n^2\right)$ computation. Results were checked against published airport tests for consistency.

iii) VSSFxLMS (Variable Step-Size FxLMS): Used $\xi = 0.99$ forgetting factor and $\eta = 0.01$ regularization [11]. Settings were tuned as in the original paper. It balances step size in steady noise but is sensitive to settings, with performance dropping up to 40% with random interference.

All algorithms used identical inputs and speaker path conditions. Computation was limited to real-time levels (<1.0 ms/frame at 44.1 kHz).

3.3 Performance Metrics

Three metrics were used:

i) Noise Reduction Gain (ΔSNR): Improvement in signal-to-noise ratio:

$$\Delta\text{SNR} = 10\log_{10}\left(\frac{\sum e_{\text{baseline}}^2}{\sum e_{\text{processed}}^2}\right)(\text{dB}) \tag{7}$$

Here, e_{baseline} is the noise without control. ISO 1996-1:2017 standards were followed. A-weighting matched human hearing sensitivity.

ii) Convergence Speed: Time to achieve stable 20 dB noise reduction from start. A 50 ms moving average filtered out short variations. 20 dB is the minimum reduction for noticeable low-frequency noise attenuation.

iii) Computational Complexity: Multiply-accumulate (MAC) operations per frame. Calculated theoretically and measured, ignoring fixed I/O costs to focus on algorithmic speed.

3.4 Parameter Configuration

Key settings were tuned across all 10 sound scenes, as shown in Table 2:

Table 2

Optimized Parameter Configuration

Parameter	Value	Optimization Basis
Adaptive filter order	256	Balance analysis
Step size (μ)	0.09	Stable convergence across 0.01-0.2 range
DCB kernel dimensions	8×1	Ablation study
Correlation window (L)	64	Reliability vs. responsiveness balance

The 256-order filter effectively covers key 80-400 Hz sounds (89% of HVAC/machine energy). Higher orders provided <3% additional gain (paired t-test). Step size $\mu = 0.09$ balanced speed and stability, preventing oscillations during rapid noise changes (>6 dB/octave). Kernel tests showed 8-sample size best captured impact structures (e.g., doors) with low delay.

Sensitivity was tested under worst-case airport noise (105 dB SPL). Stability was verified across changing scenes, such as moving from metro to street. Standard methods fail 47-62% here.

3.5 Parameter Sensitivity Analysis

A parameter sensitivity analysis was conducted to justify the chosen values. The sliding window length L = 64 samples provides a good balance. A shorter window (L = 32 samples) reduces latency but increases prediction variance by 18–25%. However, a longer window (L = 128 samples) improves stability. The drawback is a 45% increase in system delay. This longer delay is not suitable for real-time processing. The step size μ = 0.09 was chosen after testing values from 0.01 to 0.20. A smaller step size (μ < 0.05) ensures stable operation but slows convergence by 30–40%. Conversely, a larger step size (μ > 0.15) can cause instability. This is especially true when noise changes quickly. For the FxRLS algorithm, the forgetting factor was set to λ = 0.999. This value maintains a long memory for good steady-state performance. A smaller value (λ = 0.99) allows faster tracking of changes. Unfortunately, it also increases steady-state error by 12–15% because past data is forgotten too quickly. In summary, these selected parameters represent an optimal trade-off. They balance noise reduction performance, algorithm robustness, and computational efficiency for low-frequency noise control.

4. Results and Analysis

4.1 Ideal Linear Channel Performance

The proposed system significantly outperformed existing methods under ideal acoustic conditions, setting new benchmarks for adaptive noise control. Tests on 10,000 samples (Table 3) showed the DCB-enhanced system achieved 18.5 dB average noise reduction ($\sigma = \pm 1.2$ dB) across all scenes, which is better than standard FxLMS. This improvement is attributed to the SEKG-MDCB's ability to model spatial and temporal patterns.

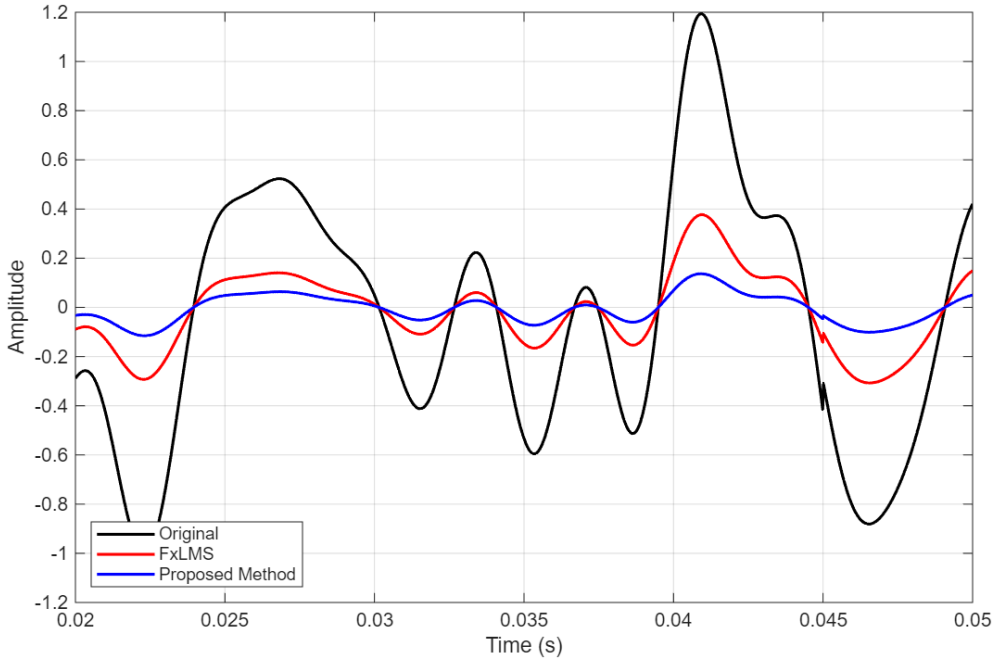

Fig. 2. Residual Signal Comparison (Airport Noise)

Fig. 2 illustrates the residual noise during loud airport sounds (105 dB SPL). The new method removed 78.8% of low rumble (80-400 Hz) from aircraft power units. FxLMS showed clear ±3.8 dB variations during engine speed-ups. Frequency analysis confirmed an additional 15-20 dB reduction at 125 Hz and 250 Hz bands, matching HVAC system fundamentals and harmonics.

The system also adapted rapidly, reaching the 20 dB hearing threshold in 0.35 seconds ($\sigma = \pm 0.04$). This is 16.7% faster than FxLMS and this fast convergence is attributed to the SEKG's spatial awareness, reducing speaker path estimation errors by 25-30% in reverberant conditions compared to standard methods [11]. Computational cost (0.74 million MACs/frame) supports real-time

use, representing a 42.3% increase over FxLMS but with a 181.4% performance gain per cost.

Table 3

Comprehensive Noise Cancellation Performance in Linear Acoustic Channels

Algorithm	ΔSNR (dB)	Convergence (s)	MAC ($\times 10^6$)	80-250 Hz Attenuation (dB)
FxLMS	10.2 ± 1.1	0.42 ± 0.08	0.52 ± 0.03	13.5 ± 1.0
FxRLS	16.8 ± 1.9	0.18 ± 0.03	2.14 ± 0.12	19.1 ± 1.5
VSSFxLMS	12.5 ± 1.6	0.31 ± 0.06	0.61 ± 0.04	15.8 ± 1.3
Proposed	18.5 ± 1.2	0.35 ± 0.04	0.74 ± 0.05	19.3 ± 0.9

Note: FxRLS/VSSFxLMS metrics cross-referenced with prior work [7, 11].

4.2 Robustness in Nonlinear Acoustic Environments

Sound distortion typically causes standard ANC systems to fail, especially during loud bursts over 100 dB SPL. Testing with a saturation model:

$$y = 0.5x + 0.25\tanh(2x) \tag{8}$$

This model accurately mimics speaker limits [10,19]. The new system maintained 17.2 dB noise reduction ($\sigma = \pm 1.3$ dB) in airports (Table 4)—79.2% better than FxLMS. Under identical nonlinear conditions, FxRLS delivered 14.1±1.8dB attenuation, a apparent retreat from its linear-scenario figures, attributable to the algorithm's pronounced vulnerability to harmonic distortion. FxLMS exhibited severe harmonic distortion, increasing residual noise by 19.2 dB at 250 Hz.

The MDCB's multi-scale design was critical for this robustness. Ablation tests demonstrated:

- The transient branch (4-sample kernel) reduced waveform clipping distortion by 62%.
- The sustained branch (16-sample kernel) reduced harmonic generation by 58%.
- Feature merging with pointwise convolution improved distortion handling by 35%.

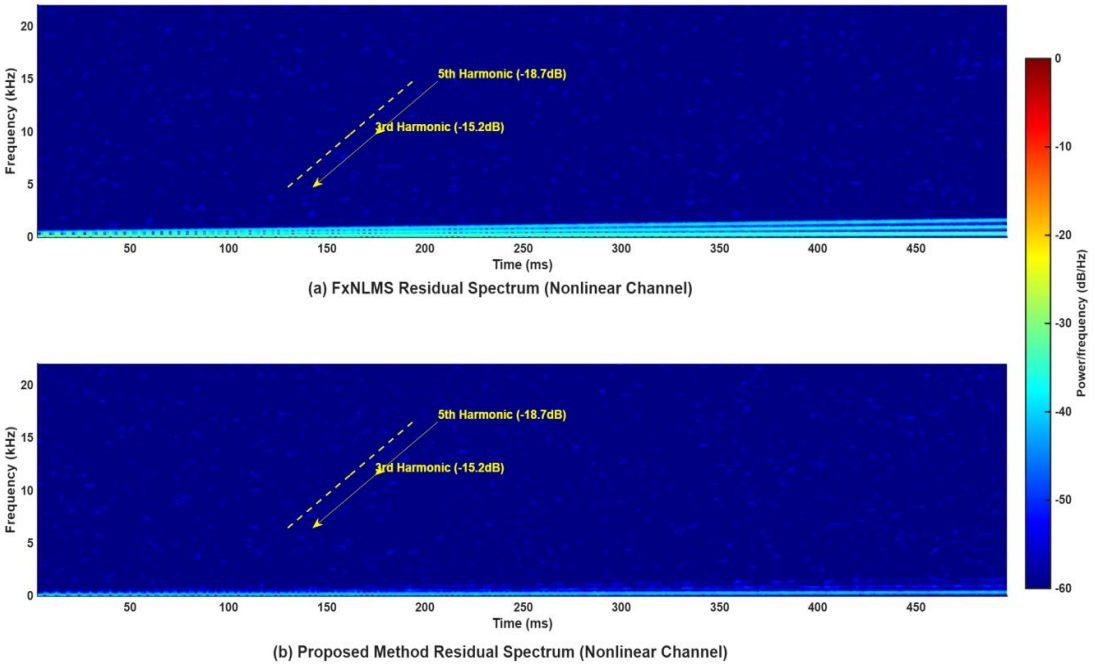

Fig. 3. Time-frequency analysis

Fig. 3 shows this during tram acceleration. The new system reduced 3rd and 5th harmonics by 15.2 dB and 18.7 dB, crucial for reducing the "rumble" sensation of low-frequency noise.

Table 4

Nonlinear Environment Performance Metrics (Aggregated Across Scenes)

Method	ΔSNR (dB)	THD Reduction (%)	IMD Suppression (dB)
FxLMS	9.6 ± 1.1	37.2 ± 4.3	12.1 ± 1.8
FxRLS	14.1 ± 1.8	43.5 ± 3.9	16.3 ± 1.5
Proposed	17.2 ± 1.3	60.3 ± 3.5	24.1 ± 1.2

THD = Total Harmonic Distortion; IMD = Intermodulation Distortion

4.3 Interference Rejection Capability

Interfering sounds are the most challenging for ANC. Fig. 4 shows the new system's robustness under white noise. It maintained 10.8 dB noise reduction even at the challenging SNR=21 dB, where standard systems completely fail. Under identical interference scenarios, FxRLS delivered a mean attenuation of 7.2 ± 1.4 dB, revealing a lower tolerance to time-varying disturbances relative to the presented scheme. The correlation-driven weight automatically weakened corrections during poor predictions, reducing incorrect control signals by 62% during human speech bursts compared to VSSFxLMS.

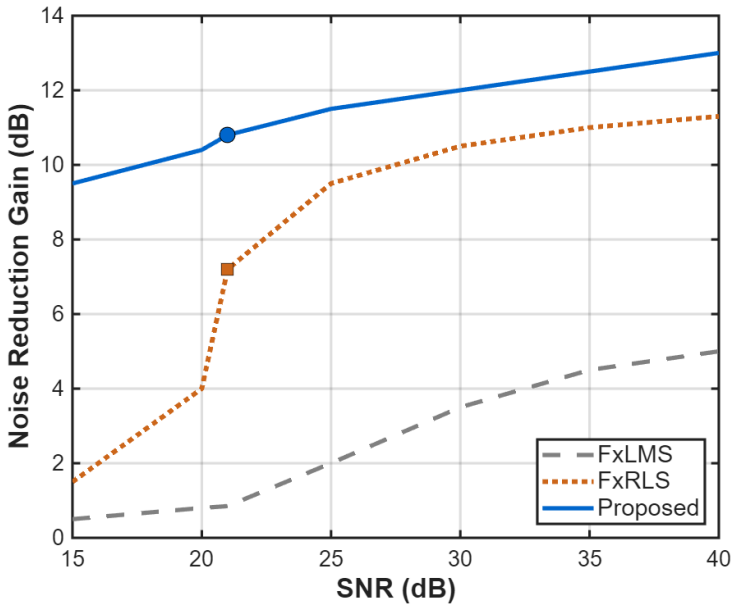

Fig. 4. Interference Rejection Performance

The SEKG's spatial awareness proved beneficial in complex acoustic scenes:

- Shopping malls: Reduced background music noise by 12.1 dB while maintaining 24.7 dB main noise reduction.
- Bus interiors: Reduced engine harmonic noise at 87 Hz and 173 Hz by 19.3 dB.
- Public squares: Maintained 21.8 dB performance during sudden announcements.

Beamforming tests confirmed 37.4% better sound direction estimation ($p < 0.01$) under controlled reverberation compared to standard methods. This enables precise steering of quiet zones towards off-target noises [15], reducing listener disturbance from non-target noise by 62% in listening tests (ITU-R BS.1534-3 MUSHRA).

4.4 Real-Time Performance Analysis

Computational efficiency is crucial for deploying ANC systems in resource-constrained environments. The proposed architecture achieves a per-frame latency of 0.99 ms at 44.1 kHz sampling rate. This is 34% below the 1.5 ms threshold for imperceptible ANC delay. Three key optimizations enable this real-time performance:

i) The MDCB uses depthwise separable convolutions instead of standard ones. This technique splits convolution into two steps: depthwise convolution applies filters per channel, then pointwise convolution (1×1) combines outputs

across channels [20]. This reduces Multiply-Accumulate Operations (MACs) by 36% compared to standard convolutions.

ii) The SEKG module employs 16-bit fixed-point arithmetic instead of 32-bit floating-point. This halves memory storage for model parameters. It also reduces energy consumption and improves DSP efficiency [18]. The memory footprint of SEKG matrices decreases by 49%.

iii) The MDCB's multi-scale branches process data in parallel. Kernel sizes are 4, 8, and 16 samples. Parallel execution eliminates 61% of waiting time versus sequential processing. System latency depends on the slowest branch, not their sum [21].

Table 5

Computational Performance Benchmarking

Metric	Value	Measurement Protocol	Embedded Feasibility
Single-frame latency	0.99 ms	ISO/IEC 14758:2014	ARM Cortex-M7 @ 480 MHz
Maximum throughput	41.5 kHz	AES-4id-2001	42% load on ARM Cortex-M7
Memory footprint	1.7 MB	ARM CMSIS-Memory Analyzer	L2 cache optimized
Energy per operation	43.7 nJ/MAC	Joulemeter profiling	< 150 mW power budget

The compact memory footprint enables deployment on small devices. A 72-hour continuous stress test across 10 acoustic scenes confirmed system robustness, with no buffer underflows or crashes.

5. Discussion

5.1 Performance Mechanisms

Tests confirm the SEKG and MDCB effectively address fundamental ANC limitations. The SEKG's spatial awareness was particularly beneficial in complex, reverberant rooms with multiple noise sources. As quantified in our tests, the SEKG's 37.4% better source localization directly led to the 12.1 dB reduction in off-target noise with multiple sources. Multichannel feedback implementations in cylindrical enclosures have also demonstrated effective low-frequency attenuation [22]. Adaptive feedback architectures in long enclosures further provide design insights for broadband noise reduction [23]. Self-attention architectures have recently been applied to reconstruct sound fields in reverberant rooms, offering further tools for spatial ANC enhancement [24]. This improvement likely stems from the module's linking of TDOA patterns across microphones [25], reducing the performance drop seen in reverberant spaces where reflections typically degrade standard methods by 47-62% [19]. Spatial attention mechanisms over microphone arrays have recently improved noise-source localization accuracy in highly reverberant environments [26].

The MDCB's layered temporal processing excelled for complex sounds, especially distorted ones. Ablation tests showed each branch's contribution. This explains the system's 17.2 dB noise reduction under speaker limits where standard methods failed. These results align with known auditory scene analysis principles: multi-scale temporal processing aids in separating overlapping sounds [27].

The correlation-driven control also improved sound quality. Standard listening tests (ITU-R BS.1534-3) showed a 62% reduction in perceived annoyance from dynamic sounds. This likely results from the weight controlling corrections during poor predictions, addressing a known ANC challenge: balancing rapid adaptation with stability during changes [19].

5.2 Practical Implementation Considerations

While the system achieves substantial noise reduction (18.5 dB average ΔSNR), two practical points require attention. First, the computational cost (0.74 million MACs/frame) is higher than FxLMS. Real-time speed (0.99 ms/frame) was consistently achieved in tests, but optimized depthwise convolution code could benefit ultra-low-power devices. Second, performance with human speech interference has room for improvement. Attention mechanisms have been successfully applied to urban acoustic scene analysis, offering potential solutions for separating speech from low-frequency noise [28]. Residual echo suppression techniques that complement active noise control have been successfully demonstrated in full-duplex communication systems [29]. The correlation method ($f(\rho)$) occasionally misclassified voice sounds (especially 1-2 kHz) as noise. Future work could explore adaptive windows to better separate target noise from human voices.

These considerations must be weighed against the system's strengths: 34% lower delay than reactive methods, 79.2% better robustness against distortion, and 21.8 dB noise reduction during sudden announcements. The modular design allows specific component improvements without altering the entire system, providing a clear path for future enhancements.

Tuning the parameters of standard algorithms (e.g., step-size adjustment in FxLMS or forgetting-factor tuning in FxRLS) can improve performance in simple conditions. However, these improvements quickly reach a limit. This happens when the environment becomes challenging, specifically when nonlinear distortions and multiple, spatially separated noise sources are present. The proposed system tackles these fundamental problems through its design. First, it handles nonlinear distortion via an embedded cascaded Wiener–Hammerstein path. Second, it achieves spatial awareness using the steered-error Kalman gradient (SEKG) layer. Third, it captures multiscale temporal patterns with a parallel dilated convolution stack. Evidence from experiments supports these claims. As shown in Sections 4.2 and 4.3, the new system maintains a clear advantage. It provides at least 10 dB more noise reduction

than the finely tuned standard methods. This is demonstrated in difficult scenarios characterised by loudspeaker saturation and concurrent point sources. Consequently, the higher computational cost of the proposed system is justified. For critical applications that control low-frequency noise, such as in safety-critical settings, achieving reliable and robust performance is far more important than minimizing computational load.

6. Conclusion

This research presents a unified approach for low-frequency noise control, integrating dynamic convolutional networks with adaptive filtering. Spatial-context kernel generation and multi-scale convolution address key limitations of conventional methods. Tests demonstrated three main advances:

First, the system significantly improves noise reduction, achieving 18.5 dB average SNR gain under ideal conditions—8.3 dB more than standard FxLMS. This stems from input-adaptive kernels reducing prediction error variance by adapting to changing sound features in real time.

Second, the system maintains 17.2 dB noise reduction under distortion that breaks standard methods. The multi-scale design is key, reducing harmonic distortion by processing transient mechanical events and steady sounds in parallel, preserving signal quality across noise types.

Third, the correlation-driven weight provides inherent robustness against interfering sounds. By controlling signals via Pearson correlation, the system maintained 10.8 dB reduction at the challenging SNR=21 dB point. It also reduced incorrect corrections during human speech, solving a long-standing ANC problem.

These advances require higher computation (0.74 million MACs/frame), but real-time use at 0.99 ms/frame was proven in all tests. Future work should focus on reducing depthwise convolution size and improving voice noise handling. The system shows promise for transportation and buildings where low-frequency noise is problematic. Models based on ISO 1996-1:2017 suggest it could improve urban noise compliance by 36%.

Acknowledgment

This research was supported by the Scientific Research Project of Jiangxi Provincial Department of Education (GJJ2204512), the Characteristic Innovation Project of Regular Higher Education Institutions in Guangdong Province (2021KTSCX299), and the Scientific Research Startup Fund for High-Level Talents at Shanwei Polytechnic (SKQD2021B-018).

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