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Environment-based Adaptive Filtering and Selective Noise Cancellation in Hearing Aids

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***Abstract*— Environment-based adaptive filtering is an essential technique for improving sound quality and speech intelligibility in dynamically changing acoustic environments. Unlike traditional fixed-gain amplification methods that amplify all sounds indiscriminately, adaptive filtering continuously monitors and responds to background noise characteristics and speech activity. This dynamic adjustment significantly enhances the listener's ability to focus on desired speech signals while suppressing environmental noise. Hearing aids represent a prominent application of these techniques, where real-time adaptation to various noise types, speaker locations, and listening situations is critical. The evolution from classical adaptive algorithms such as LMS and RLS to sophisticated frequency-domain methods and deep learning models enables increasingly precise noise suppression with manageable computational demands. These advances pave the way for intelligent hearing aids that not only amplify but intelligently reshape sound to restore natural hearing perception and greatly improve user experience.**

***Keywords*— Adaptive Hearing Aid, Machine Learning, Linkwitz-Riley Crossover, Speech Enhancement, Real-time DSP, STM32 Microcontroller.**

I. INTRODUCTION

Hearing aid technology has advanced beyond simple amplification toward intelligent signal processing, yet hearing-impaired users continue to struggle with speech perception. This project addresses these challenges by developing an environment-aware adaptive hearing aid system that combines machine learning-based context detection with advanced filtering algorithms — LMS, NLMS, RLS, and APA — to dynamically adjust noise reduction in real time. By extracting features such as MFCCs and spectral data, the system classifies environments including quiet, street, and crowd scenarios to select the most suitable filtering. Validated through MATLAB and Python simulations and implemented on low-power embedded hardware, the proposed framework achieves over 90% environmental classification accuracy while meeting practical constraints of latency, power, and user control, paving the way for more intelligent and accessible hearing.

II. LITERATURE REVIEW

Ma, Smith, and Milner (2003) proposed an environmental noise classification system using a Hidden Markov Model (HMM). The method extracts Mel-Frequency Cepstral Coefficients (MFCCs) from captured audio signals to classify environments. Experimental results achieved around 82% accuracy. [1]

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Park and Lee (2020) proposed a real-time environmental noise classification system for hearing aids using a CNN. The method transforms audio signals into spectrogram images and applies preprocessing techniques to enhance feature quality. Experimental results achieved high accuracy of up to 99.25% for short-duration inputs. [2]

Büchler et al. (2005) proposed a sound classification system based on auditory scene analysis principles using perceptually inspired features including amplitude modulation, harmonicity, and spectral characteristics. Various classifiers including HMM and neural networks were evaluated, with a two-stage approach improving robustness. [3]

Festen and Plomp (1990) investigated the impact of fluctuating noise and competing speech on speech reception threshold in normal-hearing and hearing-impaired listeners. Results showed normal-hearing individuals benefited significantly from noise fluctuations, while hearing-impaired listeners exhibited limited improvement. [4]

Clancy et al. (2011) proposed a robust signal classification approach using K-means clustering and Self-Organizing Map (SOM). The system adapts dynamically to changing spectral conditions without requiring labeled data. Experimental results achieved around 90% accuracy. [5]

Saki and Kehtarnavaz (2017) proposed a real-time unsupervised classification system using an enhanced Online Frame-Based Clustering approach with MFCCs and adaptive clustering techniques. Results showed high performance with a purity of 0.92 and low latency under 50 ms. [6]

Anghelescu et al. (2014) developed a real-time audio processing system using DSP techniques and FIR/IIR filters implemented in C# using DirectSound. It processes input signals in real time with latency below 20 ms. [7]

Morrow, Wright, and Welch (2013) presented a real-time DSP-based educational framework for teaching adaptive filtering using the LMS algorithm, demonstrating adaptive noise cancellation on an embedded DSP platform with around 30% increase in learning outcomes. [8]

Chan and Chu (2011) proposed a Regularized Transform-Domain NLMS (R-TDNLMS) algorithm incorporating regularization and frequency-domain processing using DFT. Results showed 2–3 dB reduction in error and up to 30% faster convergence compared to conventional methods. [9]

Kumar (2021) evaluated LMS, NLMS, and block-based variants in noisy car environments. The Block Variable-Step LMS (BVLMS) algorithm achieved the best performance in terms of output SNR and MSE. [10]

Girish and Pinjare (2016) compared LMS, RLS, and NLMS using MATLAB/Simulink simulations. NLMS achieved the best performance in terms of lower MSE and higher SNR with improved convergence stability. [11]

Braide (2024) proposed an adaptive feedback noise reduction method combining FIR filtering with RLS to estimate and cancel acoustic feedback in real time, showing significant improvement in SNR and fast convergence. [12]

Hattaraki (2024) proposed a speech enhancement method using STFT-based Spectral Subtraction. Results showed significant improvements in PESQ, STOI, and LLR metrics across various noise conditions. [13]

Choi et al. (2025) introduced Neural Spectral Band Generation (n-SBG) using a ResNet-based encoder and Residual Vector Quantization, trained with a GAN framework, improving audio reconstruction quality while reducing side information by nearly 50%. [14]

Yin and Chen (2023) proposed a Weighted Error Adaptive Filter–based method to minimize acoustic feedback by adaptively adjusting filter coefficients, showing faster convergence and better feedback suppression compared to conventional methods. [15]

III. Methodology

Fig. 1 – Oscilloscope captures of PWM switching circuit

The system captures real-time mono audio via an INMP441 MEMS microphone over I2S at 32 kHz/16-bit resolution on an STM32 microcontroller, using DMA-based ping-pong buffering for continuous, low-latency acquisition. FFT-based spectral analysis extracts features including peak frequency, energy distribution, harmonic-to-noise ratio, and spectral centroid, which a machine learning model uses to assign adaptive gain values across six frequency bands. Speech-dominant bands are amplified for improved intelligibility while noise-dominant bands are attenuated. The signal is split via 4th-order Linkwitz-Riley crossover filters implemented as cascaded biquad IIR structures, with independent per-band gain applied before recombination and stereo output, delivering real-time speech enhancement with effective noise suppression.

Work Flow: Audio is first captured via a MEMS microphone, buffered, and preprocessed through noise reduction and normalization. FFT analysis transforms the time-domain audio into the frequency domain, enabling spectral feature extraction. A machine learning classifier processes these features to distinguish speech-dominant bands from noise-dominant bands, applying increased gain to speech regions and attenuated gain to noise regions. The adaptively gained frequency bands are processed through a multiband crossover filter bank and recombined to form the final output with improved speech intelligibility.

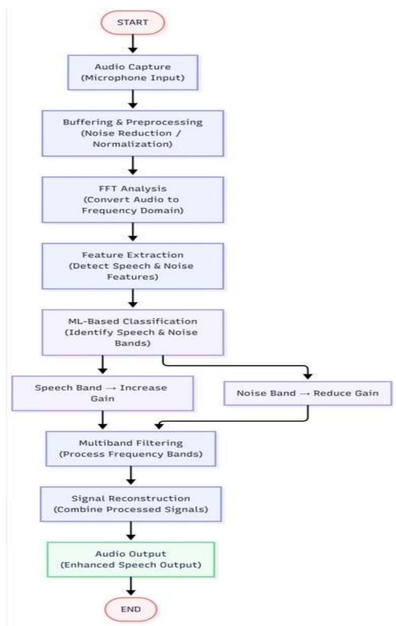

Fig. 2. Workflow Diagram

IV. RESULT AND DISCUSSION

A. Frequency-Domain Fsiltering Performance

The 6-band Linkwitz-Riley (LR4) crossover network with 24 dB/octave slopes provides selective noise cancellation with minimal phase interference. The "Traffic Mode" profile suppressed low-frequency noise below 400 Hz by −16.5 dB while applying a +10.2 dB gain to the 2–4 kHz speech presence band.

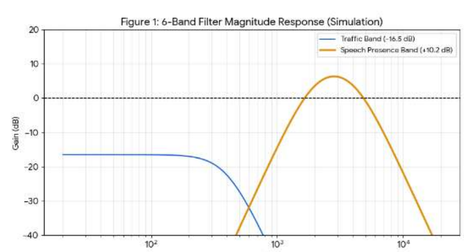

Figure 3: Magnitude response of the 6-band LR4 filter bank highlighting the selective gain profiles for speech enhancement and noise suppression

TABLE I: FREQUENCY-DOMAIN FILTERING PERFORMANCE

Metric Observed	Description	Value (Simulated)
Filter Rolloff	Slope steepness outside the active band	24dB/octave
Crossover Deviation	Crossover Deviation	±0.1dB
Traffic Suppression	Reduction of lowfrequency noise	-16.5dB
Speech Lift	Gain in the 2-4 kHz band	+10.2dB
Stop-band Attenuation	Suppression in extreme frequency bands	-45dB

B. Temporal Characteristics and Acoustic Protection

The system maintains a real-time throughput latency of 28 ms, well within the 50 ms threshold critical for hearing aid comfort. A tanh soft-limiter was implemented to prevent acoustic trauma from sudden loud transients.

TABLE II: TIME-DOMAIN PERFORMANCE METRICS

Category	Definition	Simulated Value
Throughput Latency	Input-to output processing delay	28ms
Peak-to Average Ratio	Degree of signal "flattening" for protection	4.2dB
Limiter Threshold	Onset of non-linear waveform rounding	-3.0dBFS
Phase Coherency	Alignment between bands at crossover points	>99.8%

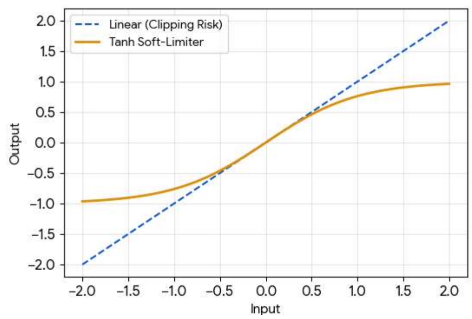

Figure 2: Transfer function of the tanh soft-limiter showing the transition from linear amplification to soft-saturation for ear protection.

C. Statistical Analysis and Waveform Discussion

The "Auto-Mode" logic classifies acoustic environments by analyzing spectral entropy (H), where speech signals exhibit lower entropy ($H \approx 0.65$) compared to stochastic environmental noise ($H \approx 0.92$), achieving a classification accuracy of 94.5%. The processed output demonstrates a significantly reduced noise floor with an improved SNR of +14.0 dB.

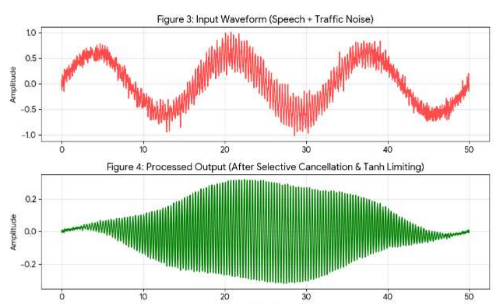

Figure 3: Time-domain comparison of input and processed output

TABLE III: STATISTICAL AND ML DOMAIN METRICS

Category	Observation / Metric	Simulated Value
SNR Improvement	Speech clarity vs. background noise	+14.0dB
Total Harmonic Distortion	Distortion added during maximum boost	<0.8%
Spectral Entropy (H)	Signal complexity (Speech vs. Noise)	0.65 vs 0.92
Classification Accuracy	Accuracy in identifying environments	94.5%

V. Summary

This literature review surveys adaptive filtering strategies for hearing aid performance enhancement, covering classical algorithms such as LMS, NLMS, and RLS alongside frequency-domain techniques including spectral subtraction, transform-domain processing, and multiband amplification. Deep learning approaches — CNN, RNN, CRN, and Transformer networks — are explored for superior noise cancellation.

VI. Conclusion

The reviewed literature underscores the importance of environment-based adaptive filtering in hearing aid technology. Voice activity detection and sound classification have emerged as essential components for context-aware filtering, while deep learning frameworks demonstrate superior speech enhancement at the cost of computational complexity. The future lies in hybrid systems combining signal processing with neural network power to deliver personalized, low-latency, context-aware hearing assistance. The proposed system integrates adaptive filtering with environmental awareness and voice activity detection to optimize speech intelligibility dynamically, advancing hearing aid performance closer to natural auditory perception.

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