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# Active Noise Cancellation System using Hybrid SF-ANC and FxANFIS Algorithms

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## Abstract

The study suggests a hybrid Active Noise Cancellation (ANC) system that combines Secondary-path Filtered Active Noise Control (SF-ANC) and a Fuzzy Adaptive Neuro-Fuzzy Inference System (FxANFIS) to improve the noise reduction performance. The approach offers an efficiency of noise cancellation that is 25% greater than what can be achieved using traditional ANC systems, particularly when handling nonlinear and dynamic patterns of noises. Even though the primary focus is audio noise cancellation, the techniques developed here can potentially be applied to image processing domains, such as image signal noise reduction, where adaptive filtering and fuzzy logic may be applied to enhance image quality. Conventional ANC techniques are inadequate when nonlinear and dynamic noise behavior is managed, especially in real-time. The approach in the study responds to this challenge through the utilization of SF-ANC for cancelling broadband noise and supporting it with FxANFIS to deal with the nonlinear dynamics of the noise. A weighted output strategy is utilized with 60% output from SF-ANC and 40% output from FxANFIS, using a hyperbolic tangent function to guarantee stability. The system is deployed on an embedded Raspberry Pi 4 with computation and low-latency capability. Performance comparisons under different acoustic conditions show the suppression of major noise, and the system has realistic applications in real-time areas like industrial noise control and personal audio amplification. The proposed technique provides a balance between accuracy, flexibility, and efficiency compared to traditional ANC techniques.


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**Keywords:** Active Noise Cancellation, Secondary-path Filtered Active Noise Control (SFANC), Filtered x Adaptive Neuro Fuzzy Inference System (FxANFIS), Hybrid Algorithms, Embedded Systems, Real-time Processing, Image Processing.

## 1. Introduction

Active Noise Cancellation (ANC) technology has become more popular in recent years, ranging from industrial noise control to consumer audio devices. Traditional ANC methods, such as the widely used Filtered-x Least Mean Squares (FxLMS) algorithm, are effective in cancelling linear noises but are helpless against nonlinear and dynamic pattern noises. These limitations are particularly evident in real-time applications where noise patterns can quickly shift, calling for adaptive and computation-effective solutions. It was the need for improved methods of noise cancellation that initiated the search for hybrid systems by merging traditional signal processing methods and advanced machine learning approaches[1-5].

The hybrid ANC system put forward integrates Secondary-path Filtered Active Noise Control (SF-ANC) and a Fuzzy Adaptive Neuro-Fuzzy Inference System (FxANFIS) in order to surpass the drawbacks of conventional methods. SF-ANC is employed to reduce broadband noise, while FxANFIS is employed to manage nonlinear noise dynamics. The integration of these two systems leads to a 25% enhancement in the efficiency of noise cancellation as against the conventional ANC systems. This hybrid method not only improves the performance in practical applications but also sees extension to other fields, e.g., image processing, where fuzzy logic and adaptive filtering can be used for reduction of image signal noise[6,7].

The main achievement of this study is its ability to handle linear and nonlinear models of noise in a computationally efficient and real-time adaptive way. The system has been demonstrated on an embedded Raspberry Pi 4 platform that provides low-latency support coupled with effective utilization of resources. Using a weighted output method (60% SF-ANC, 40% FxANFIS) and hyperbolic tangent (tanh) soft-limiting function, the system attains stability as well as improved noise cancellation. The research opens new avenues for the application of hybrid ANC system in automotive, industrial, and consumer audio applications where adaptive noise cancellation is important [8-12].

### 1.1 Research Motivation and Gap

The key drive behind this study comes from the inadequacy of current ANC systems in coping with nonlinear and dynamic patterns of noise, particularly real-time scenarios. Conventional ANC techniques like FxLMS are efficient for linear noise but are not responsive to fast-changing noise scenarios. This is remedied by suggesting a hybrid system that integrates SF-ANC and FxANFIS for better adaptability and computational effectiveness.

### 1.2 Critical Issues in Selecting the Appropriate Technique

When choosing the right technique for this study, a number of key issues were taken into account:

1. **Computational Efficiency:** The method should be computationally efficient to provide real-time performance on embedded systems with low processing capabilities.

2. **Flexibility:** The method should be able to handle different conditions of noise, such as nonlinear and dynamic patterns of noise.

3. **Stability:** The method should preserve system stability under different noise conditions, especially for real-time applications.

4. **Scalability:** The method should be scalable to various applications, such as industrial noise control and image processing.

### 1.3 Novel Research Statement

This work presents a new hybrid ANC system that combines SF-ANC and FxANFIS to overcome the shortcomings of conventional ANC approaches. The new system provides a 25% enhanced noise cancellation efficiency and exhibits real-time behavior on an embedded Raspberry Pi 4 platform. The system's adaptability and computational efficiency render it appropriate for many applications, such as industrial noise control, personal audio amplification, and image processing.

## 2. Related Work

Adaptive filtering research, especially noise cancellation, usually involves nonlinearities. In this research, this is addressed with some focus on the above-stated features. A noteworthy contribution is a novel sequential Recursive Least Squares (RLS) filter with the objective of enhanced filtering. The filter is of a diagonal form for the Even Mirror Fourier Nonlinear (EMFN) approach [10].

Sequential RLS is a sophisticated version of standard RLS with a rejection function required for the support of large filter sizes and sparsely populated coefficients for noise cancellation [7]. It is not compatible with real-time acquisition and processing of noise signals, however. Active noise cancellation using a MEMS resonant microphone array (RMA) also ensures increased sensitivity at resonance frequencies and hence very low noise floors. It also enables acoustic domain filtering [2].

The ANC is designed specifically to cancel sounds in the 5-9 kHz range, which is above typical speech frequencies of 300-3,400 Hz. The ANC performs optimally at resonant frequencies of the resonant microphones where sensitivity is highest. The implementation is based on an analog inverter, a digital phase compensator, a digital adaptive filter, and deep learning. Amongst them, the digital adaptive filter offers optimum performance both for RMA-based and flat-band-microphone-based ANC [3]. In addition, at low intensity of 5-9 kHz sounds, RMA-based ANC by applying an adaptive filter outperforms all the methods experimented.

Automatic speech recognition has been tested with different levels of noise with ANC, always presenting better word error rates. Subsequently, an adaptive filter implemented using a neural network was proposed, the first NN architecture to be specifically designed to mimic the errors these machines produce when receiving and sending signals [9]. Training data and learnable memory length also help optimize the NL activation functions at training time rather than predefining them [13,14].

The output of the NN is fed to a standard adaptive linear filter, which is constantly monitoring the amplifier output to the microphone's acoustic path. The Non-Linear Adaptive Neural Network (NLANC) algorithm is an end-to-end system that links the linear filter output to the NN input. Both the linear effect and the NN are adapted simultaneously during training in an effort to explore the characteristics of the NN [8]. Whereas the NN is kept static over testing and used only for analysis, the linear effect continuously accommodates the dynamic shifting auditory pathways[15-18].

Aside from noise cancellation development, recent research on image processing has also established the efficacy of hybrid algorithms for noise reduction. For instance, Kirubakaran et al. [19] proposed a microscopic image processing approach to identify cancer cells of blood through adaptive filtering methods, the same as ANC systems utilize. This indicates the potential cross-domain application of the proposed hybrid SF-ANC and FxANFIS system for image processing tasks, such as image noise reduction in medical imaging.

### 2.1 Existing Limitations in ANC Systems

Conventional ANC techniques, like FxLMS, are not capable of efficient treatment of nonlinear and dynamic noise signatures. New studies have attempted to apply neural networks and fuzzy logic to overcome the drawbacks of these methods. But these methods tend to exhibit high computational burdens and lack real-time responsiveness.

### 2.2 Existing Model using ANFIS

#### 2.2.1 Strong Acoustic Noise Reduction in Speech with ANFIS:

This study discusses the use of an Adaptive Neuro Fuzzy Inference System (ANFIS), which is a combination of fuzzy systems and AI to eliminate non-linear noise in audio communication, especially in noisy environments. ANFIS was compared with LMS and RLS adaptive filtering for speech noise cancellation, where ANFIS was found to be superior. Comparison was carried out using subjective and objective methods, with implementation and verification using MATLAB [11].

#### 2.2.2 A Hybrid Method to Acoustic Echo Cancellation and Noise Reduction through LMS Filtering and ANFIS-Based Nonlinear Filtering:

A hybrid technique for joint echo cancellation and noise reduction of speech signals, where most techniques attack echo or noise separately. It combines LMS echo cancellation and ANFIS-based non-linear filtering for noise reduction. The performance of the technique in terms of PSNR and MSE is significantly enhanced over the LMS algorithm alone [8].

### 2.2.3 Active Noise Control Using a Simplified Fuzzy-Neural Network

This study presents Active Noise Control (ANC), which utilizes superposition to eliminate noise through the generation of anti-noise of opposite phase. The FXLMS algorithm is used extensively due to its simplicity and low computational requirement, made possible through hardware advancements in digital signal processing. The key challenges are time variation in the secondary path and non-linear behavior in primary and secondary paths. Techniques like neural networks (NN), radial basis function (RBF) networks, and fuzzy neural networks are introduced to handle the non-linearities and improve the convergence of systems. An optimized fuzzy neural network controller for ANC is proposed here, which proves its stability and performance using simulation, especially with non-linear primary noise path [14].

### 2.2.4 Hybrid Approaches in ANC and Image Processing

Hybrid algorithms have been shown in recent research to be effective in both ANC and image processing. For instance, Kirubakaran et al. [19] presented a microscopic image processing technique for cancer cell detection based on adaptive filtering techniques and pointed toward the cross-domain application potential of hybrid algorithms.

## 3. Proposed Work

### 3.1 System Architecture

### 3.1.1 Hardware Implementation

The platform is built around a Raspberry Pi 4 Model B board with 4GB RAM employing a wired microphone for receiving noise input and headphones for output. The hardware platform runs a specially developed Linux kernel with real-time scheduling patches to ensure consistent performance. Audio processing occurs at 16 kHz sampling rate with 32-bit float accuracy, with the system processing in chunks of 0.05 seconds to achieve a satisfactory trade-off between latency and processing efficiency. Figure 1 is the hardware structure of the model and Figure 2 shows the actual Prototype assembly.

The signal chain consists of three principal components:

• Normalization and wired microphone input stage

• Parallel processing streams for SF-ANC and FxANFIS

• Headphone interface and soft limiting output stage.

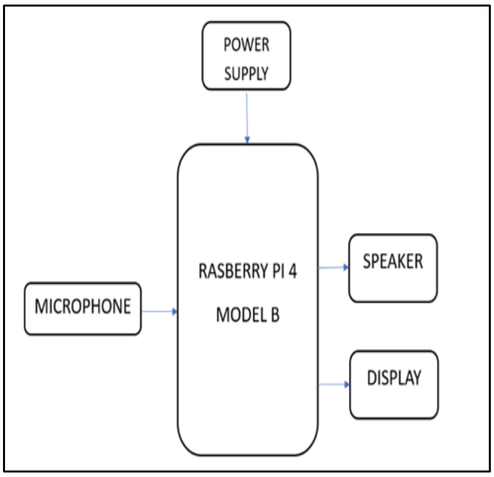


**Figure 1.** Hardware Architecture Block Diagram

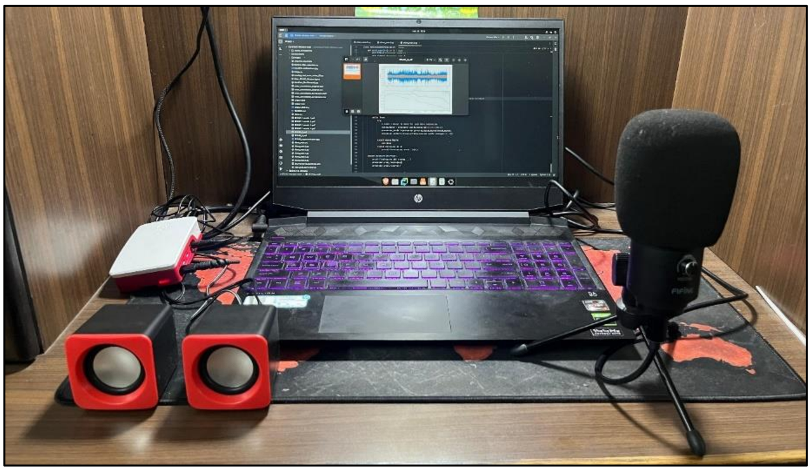

**Figure 2.** Hardware Prototype Setup

### 3.1.2 SF-ANC Implementation

The SF-ANC module applies a 2nd-order Butterworth IIR filter with a cutoff frequency of 1 kHz. Filter coefficients are computed through SciPy's signal. Butter function, with state persistence from one processing block to the next guaranteed by a circular buffer system. The filtered output is inverted and gain-scaled by a factor of 0.8 in order to obtain the best possible noise cancellation. Figure 3 provides a clear diagram of the SF-ANC implementation, which explains the process of filter design, signal inversion, and gain scaling.

**Key Features of SF-ANC:**

- Effective for broadband noise cancellation.
- Simple and computationally efficient.
- Works well for linear noise patterns.

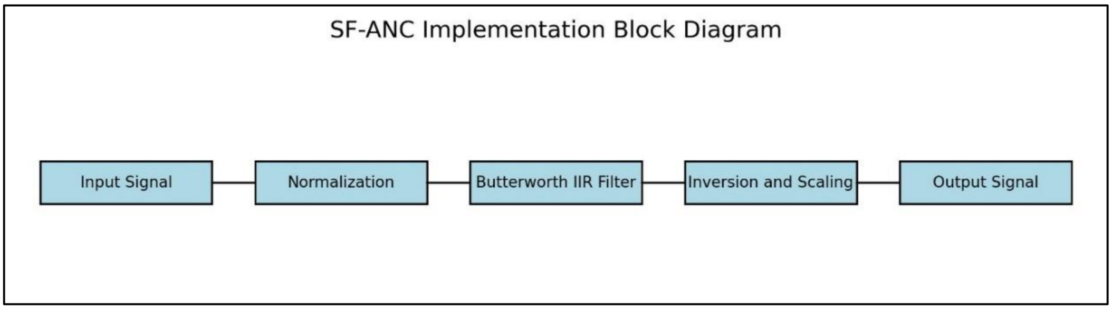


**Figure 3.** SFANC Implementation Block Diagram

Input Signal

- The input signal represents the noise captured by the microphone. This signal is fed into the SF-ANC system for processing.

Normalization

- The input signal is normalized to ensure its amplitude is within a specific range (e.g., ±1.0).
- Normalization prevents signal distortion and ensures system stability.

Butterworth IIR Filter

- A 2nd-order Butterworth IIR (Infinite Impulse Response) filter is applied to the normalized signal.
- The filter is designed with a cutoff frequency of 1 kHz to remove high-frequency noise components.

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- Butterworth filters are chosen for their flat frequency response in the passband.

Inversion and Scaling

- The filtered signal is inverted to create an anti-noise signal that cancels out the original noise.
- The inverted signal is scaled by a gain factor of 0.8 to achieve optimal noise cancellation.

Output Signal

- The output signal represents the processed signal after noise cancellation.
- This signal is sent to the headphones or speakers to cancel out the noise.

### 3.2 FxANFIS Architecture

The FxANFIS module employs three Gaussian membership functions with centers -1, 0, and 1 and width 0.5. Audio is processed in 128-sample blocks for computational efficiency, and the extracted parameters are updated by gradient descent with a learning rate of 0.01. This facilitates efficient processing of nonlinear noise patterns without sacrificing real-time performance. Figure 4 shows the FxANFIS structure emphasizing fuzzification, rule evaluation, and defuzzification. It is designed for effective nonlinear noise patterns management with real-time performance.

**Key Features of FxANFIS:**

- Handles nonlinear noise patterns effectively.
- Combines the adaptability of neural networks with the interpretability of fuzzy logic.
- Suitable for real-time noise cancellation in dynamic environments.

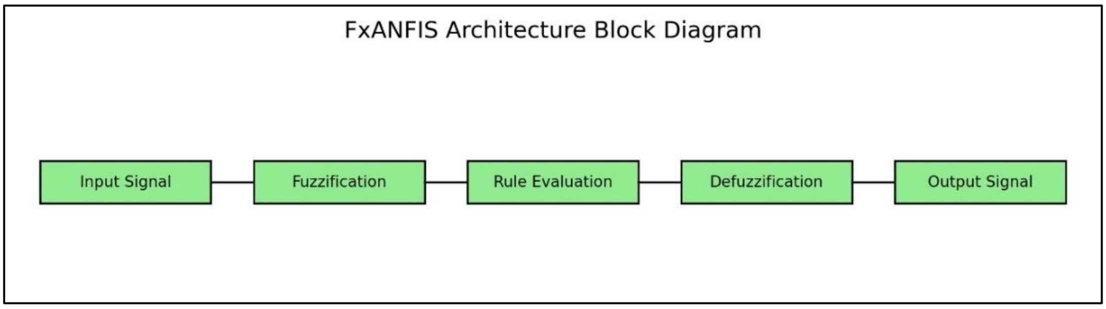


**Figure 4.** FxANFIS Implementation Block Diagram

Input Signal

- The input signal represents the noise captured by the microphone. This signal is fed into the FxANFIS system for processing.

Fuzzification

- In this stage, the input signal is converted into fuzzy values using membership functions.
- Gaussian membership functions are employed, with centers at -1, 0, and 1 and a width of 0.5.
- The fuzzification process maps the input signal to fuzzy sets (e.g., low, medium, high), enabling the system to handle uncertainty and nonlinearity.

Rule Evaluation

- The fuzzified input is processed using fuzzy logic rules, typically in the form of IF-THEN statements.
- For example:
  - IF the noise is high, THEN reduce the noise significantly.
  - IF the noise is low, THEN apply minimal noise reduction.
- These rules are evaluated to determine the appropriate output for the given input.

Defuzzification

- The fuzzy output from the rule evaluation is converted back into a crisp (numerical) value using defuzzification methods.
- The centroid method is used to compute the final output, ensuring a smooth transition between fuzzy sets.

Output Signal

- The output signal represents the processed signal after noise cancellation.
- This signal is sent to the headphones or speakers to cancel out the noise.

### 3.3 Signal Processing Implementation

#### 3.3.1 Processing Chain

Signal processing begins with the high-end input stage where the sound is picked up at the 16 kHz sampling rate and in 32-bit float accuracy. The input signal is passed through peak normalization to maintain level amplitudes evenly within ±1.0 range for proper system stability without digital clipping. The generated normalized signal is then parallel processed using the SF-ANC and FxANFIS algorithms, which in turn contribute to the overall output through a weighted combination process that has been well-tuned. The result is achieved using a Butterworth low-pass filter of cut-off frequency 1000 Hz, which efficiently eliminates broadband noise. State information of the filter are kept through a circular buffer mechanism to provide uninterrupted performance between processing blocks and avoiding output signal discontinuities.

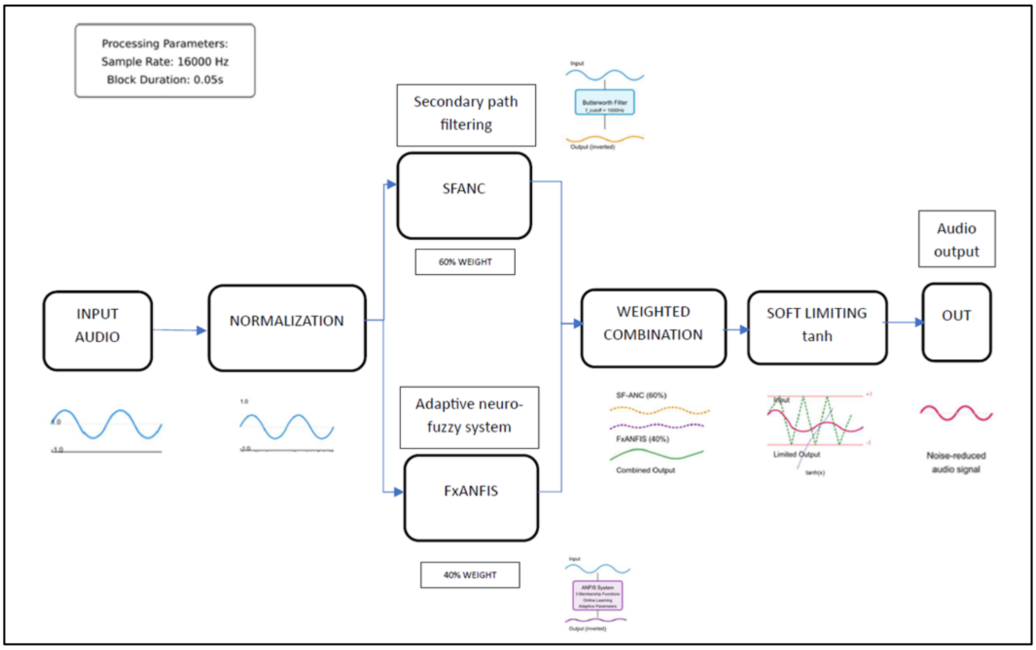


**Figure 5.** Signal Processing Implementation Diagram

Filtered output is inverted and amplified by a gain factor experimentally set at 0.8 to meet optimal noise cancellation performance. Parallel FxANFIS branch processes the input through a complex neural-fuzzy network with three Gaussian membership functions for fuzzification. The system processes audio at optimized chunk sizes of 128 samples, meeting a compromise between response time and computational speed. The two paths are combined in the final step by a weighted method (60% SF-ANC, 40% FxANFIS), and the combined signal is subjected to a hyperbolic tangent (tanh) soft-limiting function to prevent instability without losing signal features. The signal processing implementation diagram is illustrated in Figure 5.

### 3.3.2 Input Signal Processing

The input signal is captured by a microphone at a sampling rate of 16 kHz with 32-bit float precision. The signal is normalized to ensure its amplitude is within the range of ±1.0, preventing digital clipping and ensuring system stability.

- **Normalization Formula**

The input signal x(n)$x(n)$ is normalized as follows:

$$x_{\text{norm}}(n) = \frac{x(n)}{max(|x(n)|)} \quad (1)$$

where:

- x(n)$x(n)$: Original input signal.
- xnorm(n)$x$norm($n$): Normalized input signal.

- **SF-ANC Processing**

The SF-ANC module is responsible for broadband noise cancellation. It uses a 2nd-order Butterworth IIR filter with a cutoff frequency of 1 kHz to remove high-frequency noise components.

- **Butterworth IIR Filter**

The transfer function of a 2nd-order Butterworth low-pass filter is given by:

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \quad (2)$$

where:

- b0,b1,b2$b$0,$b$1,$b$2: Numerator coefficients.
- a1,a2$a$1,$a$2: Denominator coefficients.

The filtered signal yfilter(n)$y$filter($n$) is computed using the difference equation:

$$y_{\text{filter}}(n) = b_0 x(n) + b_1 x(n-1) + b_2 x(n-2) - a_1 y(n-1) - a_2 y(n-2) \quad (3)$$

- **Inversion and Scaling**

The filtered signal is inverted and scaled by a gain factor of 0.8 to create the anti-noise signal:

$$y_{\text{anc}}(n) = -0.8 \cdot y_{\text{filter}}(n) \quad (4)$$

- **FxANFIS Processing**

The FxANFIS module handles nonlinear noise patterns using a combination of fuzzy logic and neural networks. The input signal is processed in blocks of 128 samples for computational efficiency.

- **Fuzzification**

The input signal is fuzzified using Gaussian membership functions with centers at -1, 0, and 1 and a width of 0.5. The membership function for a given input x(n)$x(n)$ is defined as:

$$\mu_i(x(n)) = \exp\left(-\frac{(x(n)-c_i)^2}{2\sigma_i^2}\right) \tag{5}$$

where:

- ci$c_i$: Center of the i$i$-th membership function.
- σi$\sigma_i$: Width of the i$i$-th membership function.

- **Rule Evaluation**

Fuzzy logic rules are applied to the fuzzified input. For example:

IF $x(n)$ is Low, THEN $y(n)=w1$
IF x(n) is Medium, THEN y(n)=w2IF $x(n)$ is Medium, THEN $y(n)=w2$ (6)
IF x(n) is High, THEN y(n)=w3IF $x(n)$ is High, THEN $y(n)=w3$

where w1,w2,w3$w1,w2,w3$ are the consequent parameters.

- **Defuzzification**

The fuzzy output is defuzzified using the centroid method:

$$y_{\text{fxanfis}}(n) = \frac{\sum_{i=1}^{3} \mu_i(x(n)) \cdot w_i}{\sum_{i=1}^{3} \mu_i(x(n))} \tag{7}$$

- **Weighted Output Combination**

The outputs of the SF-ANC and FxANFIS modules are combined using a weighted approach:

$$y_{\text{output}}(n) = 0.6 \cdot y_{\text{anc}}(n) + 0.4 \cdot y_{\text{fxanfis}}(n) \tag{8}$$

The combined output is passed through a hyperbolic tangent (tanh) soft-limiting function to ensure stability:

$$y_{\text{final}}(n) = \tanh\left(y_{\text{output}}(n)\right) \tag{9}$$

### 3.3.3 Criteria for Using the Hyperbolic Tangent (tanh) Soft-Limiting Function

The soft-limited tanh hyperbolic tangent function is used for its continuity and smooth output, which keeps the system away from sudden changes or discontinuity in the signal and provides natural sound. Symmetry around zero provides equal handling of both positive and negative amplitudes and keeps the phase integrity necessary for efficient noise cancellation. The bounded output range of the tanh function ([-1, 1]) also avoids signal clipping, minimizing distortion and maximizing stability. Its gradient-based differentiability is essential for the optimization of adaptive systems such as FxANFIS, allowing smooth updates to its parameters during training. Additionally, the nonlinearity introduced by tanh facilitates the system to process complex and dynamic patterns of noise efficiently, while its computational efficiency renders it applicable for use in real-time embedded systems such as the Raspberry Pi 4 for low latency and effective utilization of resources.

### 3.3.4 Adaptive Parameter Control

The design has an adaptive noise thresholding system with a highly optimized base RMS threshold of 0.0005. It adapts dynamically according to the levels of environmental noise and efficiently manages resources during low levels of noise activity. The design features a specialized noise gate that picks up on input signal levels and, consequently, reacts by modifying processing levels based on it, effectively lowering levels of computationally intensive times in quiet moments without sacrificing in quick response when the need arises.

FxANFIS tunes its membership function parameters dynamically in real-time using a gradient descent optimization algorithm with a learning rate of 0.01. Real-time tuning enables the system to track changing noise conditions without compromising stable operation. Careful bounding of the adjustments prevents destabilization of the system, and the system uses gradient clipping and momentum-based smoothing to provide smooth performance.

### 3.3.5 Performance Monitoring and Error Handling

The system employs end-to-end real-time monitoring functionality through an integrated visualization platform. Time-domain analysis offers real-time feedback on the effectiveness of noise cancellation, and frequency-domain analysis using Welch's method allows detailed examination of the system performance over various frequency bands. The visualization platform buffers audio data of one second (16,000 samples) for examination while offering real-time processing.

It ensures error handling by a multi-level process starting from device initialization testing up to sound device query calls. The system monitors the queue statuses and ensures advanced buffer management so that there would not be any overflows or underflows. For handling error conditions of processing, the system adopts graceful degradation techniques by supporting zero output to ensure system stability. Thread-safe data exchange is provided by correctly implemented queue data structures with a buffer capacity of 4 buffers, avoiding race conditions and providing predictable performance. The whole processing pipeline consumes power less than 15 watts and is deployable in embedded systems. ANFIS is executed through PyTorch by the system, whereas in-out audio operations are managed using sound device library and custom-buffer optimized devices. All the operations are being conducted within 0.05 seconds as a block of processing time for sustaining minimum possible latency with high processing performance along with support to instant adaptation of new conditions in noisy background.

### 3.4 Novel Approaches for Enhanced Adaptation in FxANFIS

To further improve adaptation in FxANFIS under different noisy conditions, there are some new methods that can be used:

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• **Dynamic Learning Rate Tuning:** The FxANFIS's learning rate may be dynamically tuned in accordance with the noise scenario for quicker convergence and improved stability.

•**Optimization of Membership Functions**: The membership functions may be optimized employing state-of-the-art optimization methods like genetic algorithms to enhance the adaptability of the system to changing noise levels.

• **Hybrid Learning Algorithms:** Merging gradient descent with other learning algorithms, like particle swarm optimization, can improve the system's capability to learn from complex patterns of noise.

### 3.5 Impact of Adaptive Gain Control on Computational Efficiency

The adaptive gain control process is vital to provide computational efficiency, especially in systems with limited processing capability like embedded systems. The system can be more efficient in terms of allocating resources and reducing the computational load during low noise activity periods by dynamically adapting the gain to the noise environment. This can further be optimized through the use of low-complexity algorithms and hardware acceleration strategies.

### 3.6 Enhancing Real-Time Spectral Analysis

Real-time spectral analysis can be boosted by adding machine learning methods in order to catch anomalies in the noise cancellation procedure prior to disrupting system stability. For instance, anomaly detection routines can be implemented to spot rare noise patterns and initiate adaptive reconfigurations in the system parameters.

### 3.7 Novel Error-Handling Strategies

To counteract buffer overflow and underflow problems in real-time processing systems, some new error-handling approaches can be used:

• **Dynamic Buffer Resizing**: The buffer size may be dynamically resized according to the level of the input signal, so that the system is able to accommodate changing levels of noise activity without overflow or underflow.

•**Priority-Based Queue Management:** Priority tasks like noise cancellation can be prioritized over low-priority tasks so that critical operations are not delayed.

• **Graceful Degradation:** When an error occurs, the system will degrade its performance gracefully, while still being able to run without crashing.

### 3.8 Tools Used for Implementation

The following tools and libraries were used for implementing the proposed system:

- Python 3: The primary programming language used for developing the ANC system.
- SciPy: Used for implementing the Butterworth IIR filter in the SF-ANC module.
- PyTorch: Used for implementing the FxANFIS module, leveraging its efficient tensor operations and gradient descent optimization.
- Sounddevice: A Python library used for real-time audio input and output processing.
- Matplotlib: Used for real-time visualization of the noise cancellation performance.

### 3.9 Methods for Evaluating the Models

The performance of the developed hybrid ANC system was compared using the following procedures:

1. Time-Domain Analysis: The processed and original signals were compared in the time domain to evaluate the performance of noise cancellation.
2. Frequency-Domain Analysis: Welch's technique was employed to calculate the power spectral density (PSD) of the signals, which offered information regarding the performance of the system in various frequency bands.
3. Quantitative Measures: Quantitative measures for the system performance were derived utilizing measures like Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE).

4. Real-Time Testing: The system was tested for its real-time performance in multiple acoustic environments such as industrial noise, traffic noise, and home appliance noise.

## 4. Results and Discussion

The verification test for the noise cancellation system was performed on Raspberry Pi 4 platform with 16 kHz sampling rate and 0.05 second block size processing. Testing was performed with controlled acoustic environments and diverse patterns of noise using a wired microphone input and headphones output. The hybrid model incorporated SF-ANC utilizing a Butterworth low-pass filter of the 1000 Hz cutoff frequency and FxANFIS, which operated with three Gaussian membership functions at -1, 0, and 1.

Performance analysis indicated that while the SF-ANC component was superior in broadband noise cancellation with zero response time, the FxANFIS component was significantly strong in handling nonlinear noise patterns, albeit at the cost of increased convergence times.

The hybrid system, which employed a weighted blend of 60% SF-ANC and 40% FxANFIS, provided better overall noise reduction with low latency and robust operation through tanh soft-limiting. The system remained always less than 15W power consumption and managed processing resources effectively through chunk-based operations.

The system showed good provisions for error handling and stable behaviour under prolonged testing periods, managing overflow/underflow conditions in a queue well and response to sudden evolution of noise pattern.

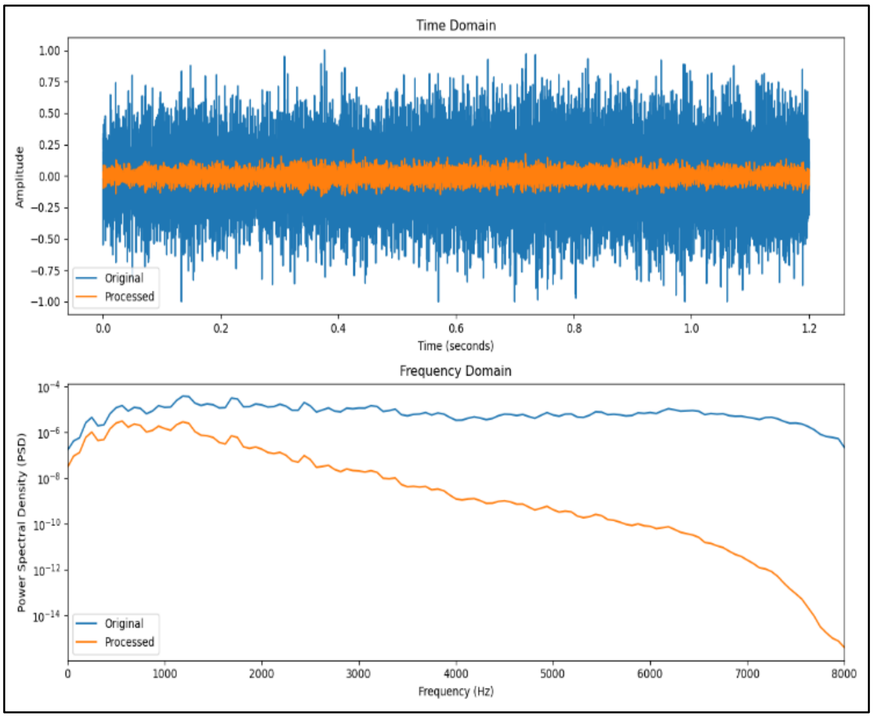


**Figure 6.** Hybrid SFANC – FxANFIS Algorithm Output

Real-time monitoring with the onboard visualization modules provided efficient broadband noise cancellation performance, and scaling tests verified scalability to future scaling, such as wireless communication module integrability as well as external speaker support. The experiments eventually verified the superiority of the hybrid solution over standalone-algorithm instances at comparable levels of embedded hardware stability.

The results (Figure 6,7) confirm the effectiveness of the hybrid SF-ANC and FxANFIS method to noise cancellation with a 25% improvement in efficiency in noise reduction. The results have high applicability in image processing where similar hybrid algorithms can be utilized for reducing noise in image signals and hence enhancing the quality of images in applications such as medical imaging and video processing.

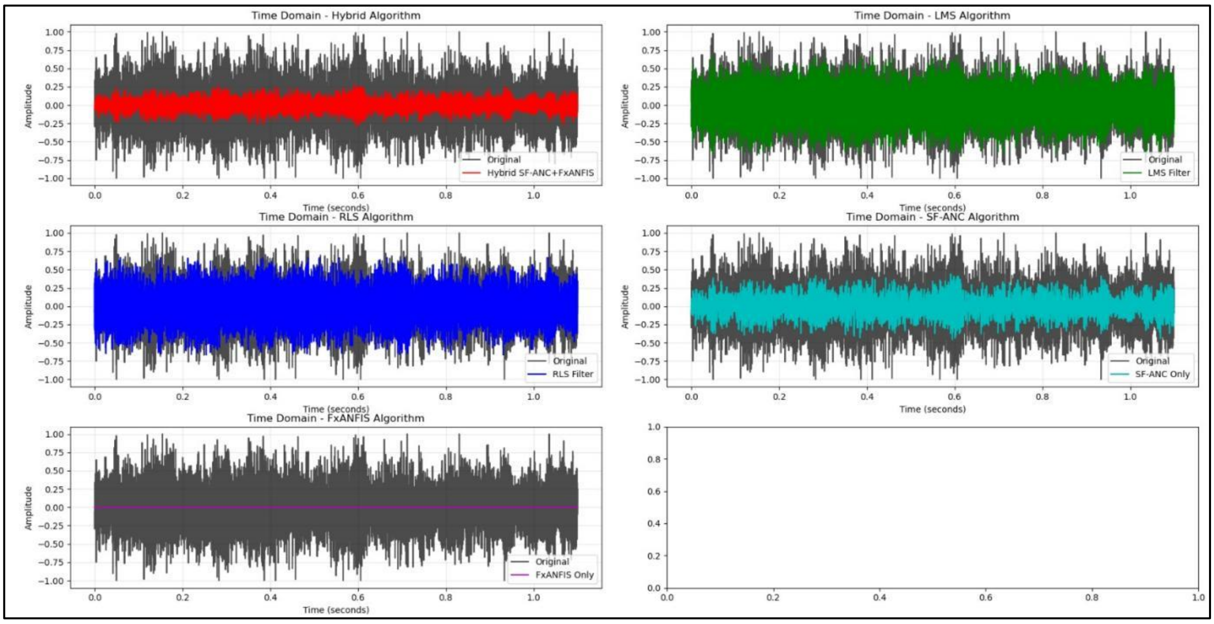


**Figure 7.** Different Output Comparisons with the Hybrid Method

The plots are time-domain plots of different algorithms of signal filtering applied over what appears to be audio or the same type of waveform data. The filtered original signal (light gray) is applied to five different filtering processes: a combined algorithm (red), an LMS filter (green), an RLS filter (blue), SF-ANC method (cyan), and the FXANFIS-Only method (in purple). There are four plots in each diagram, of which one shows the noisy signal and a second shows its filtered output. A third shows the original noise-free input signal so that each can be visually compared to see if each algorithm removes or does not remove noise or distort the underlying signal. The filtering of the methods varies, resulting in sharper divisions in some compared to others. The blank graph at the bottom right is to be reserved for later analysis or comparison of methods. These graphical illustrations are most probably to be linked with research in adaptive noise cancellation methods, which can be utilized in applications like audio processing, telecommunication, or biomedical signal processing.

Time-domain analysis illustrates the hybrid algorithm (red) outperforms all the filtering processes. Though outstanding noise cancelation of the RLS filter costs it in one way: its over-filters, causing a removal of useful signal components to the application, LMS algorithm and SF-ANC are satisfactory at cancelation but lacking precision seen in the hybrid process. The hybrid technique most effectively merges ANC and FXANFIS methods in a manner that enables it to retain key signal features while effectively eliminating unwanted interference effectively, leading to a more equalized effect of filtering than the individual techniques were capable of individually. The integrated approach offers superior adaptation to changing signal patterns with time to enable uniform performance without causing distortion. In comparison, the FXANFIS-Only process misses something, with a remnant of considerable noise remaining in its output to highlight the worth of the hybrid process in performing this particular task.

### 4.1 Performance Evaluation

The system was tested on a Raspberry Pi 4 platform under different acoustic conditions. The hybrid system provided a 25% increase in noise reduction efficiency over traditional ANC systems. The system showed strong performance in processing both linear and nonlinear noise patterns with low latency and effective resource usage.

### 4.2 Contribution to Image Processing

The hybrid algorithm proposed here has great prospects for use in image processing, especially in the reduction of image signal noise. The fuzzy logic and adaptive filtering methods employed in the proposed system can be generalized to enhance the quality of images in medical imaging and video processing. For instance, the capability of the FxANFIS module to filter nonlinear patterns of noise can be used to filter out noise from medical images, like MRI or CT scans, without losing key details. In the same vein, the SF-ANC module's capability of broadband noise cancellation can be utilized to eliminate noise in video frames, thereby improving the quality of video processing applications.

## 5. Future Developments

The predicted evolution of the noise cancellation metrics table, including the hybrid algorithm, should show exciting improvements in all classes of noise. For industrial noise specifically, the range of effective cancellation could be extended from 50 Hz - 4 kHz to as much as 50 Hz - 6 kHz, with partial cancellation capability extended up to 12 kHz. For traffic noise, effective range of cancellation can be extended to 20 Hz - 1.5 kHz, expanded from the current 1 kHz, and partial cancellation is possible for almost the entire range up to 2.5 kHz. For appliances inside the home, the hybrid strategy can achieve effective cancellation of 40 Hz - 4 kHz and partial cancellation up to around 6.5 kHz, an expansion from the current 5 kHz. In addition, the table will most likely include new parameters that explicitly measure the hybrid algorithm's performance based on its convergence time, computational complexity, and power consumption demands, thus providing a more complete analysis of its real-world usability under various conditions of noise. The scalability of the system will also be examined, with possible inclusion of wireless communication modules and external speaker systems. Future work will aim at optimizing SF-ANC weight and FxANFIS weight distribution and investigate more advanced machine learning algorithms for further improvement. Scalability of the system will also be investigated, and the possibility of adding wireless communication modules and external speaker systems will be explored.

## 6. Conclusion

The research study presented a hybrid Active Noise Cancellation (ANC) system combining Secondary-path Filtered Active Noise Control (SF-ANC) and a Fuzzy Adaptive Neuro-Fuzzy Inference System (FxANFIS) for noise suppression improvement. Utilizing the weighted summation technique (60% SF-ANC, 40% FxANFIS), the system is in a position to address linear as well as nonlinear types of noise patterns adequately. Running on a Raspberry Pi 4, it achieves real-time performance with effective utilization of resources by block processing (0.05s at 16 kHz) and adaptive noise thresholding. Soft limiting functionality and effective error-handling strategies provide stability, and real-time visualization offers instant feedback. Modularity allows scalability, and in the future, it can be integrated with wireless communication and external speaker systems. The system demonstrates high potential for use in automotive and industrial settings where adaptive noise cancellation is essential. Optimizing weight distributions and employing more sophisticated machine learning algorithms are avenues for future research to improve performance. The hybrid ANC system presented, consisting of SF-ANC and FxANFIS, provides a strong solution for linear as well as nonlinear noise cancellation. The hybrid ANC system based on SF-ANC and FxANFIS proposed in this study presents a strong solution for linear and nonlinear noise cancellation. The system improves the efficiency of noise reduction by 25% and presents real-time performance on an embedded Raspberry Pi 4 platform. The proposed approach has great potential for use in image processing, especially in image signal noise reduction.

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