A Project report on

Implementation of Active Noise Cancellation using Adaptive Filters

Submitted in partial fulfilment of the requirements for the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS & COMMUNICATION ENGINEERING

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BONAFIDE CERTIFICATE

This is to certify that the project titled **Implementation of Active Noise Cancellation using Adaptive Filters** is a bonafide record of the work done by

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ABSTRACT

Active noise cancellation (ANC) systems employ adaptive filtering techniques to generate an anti-noise signal that effectively cancels out unwanted acoustic disturbances. This project comprehensively investigates the performance of various adaptive filtering algorithms, including the Normalised Least Mean Squares (NLMS), Filtered-x LMS (FxLMS), Recursive Least Squares (RLS), Filtered-u LMS (FuLMS), and Feedback ANC for ANC applications through simulations. A detailed literature review was conducted to understand the strengths, weaknesses, and applicability of each algorithm. The methodology involved algorithm implementation, system modelling of primary and secondary paths, parameter tuning, and performance evaluation under diverse signal and noise conditions. Key metrics such as signal-to-noise ratio (SNR), mean squared error (MSE), and convergence speed were analysed. The research findings compare the algorithms' robustness to signal variations, noise characteristics, and parameter sensitivity. Furthermore, the study explores the potential of hybrid filters, combining the advantages of multiple algorithms like FxLMS and Feedback ANC, to enhance noise cancellation performance. The results provide valuable insights into the suitability of different adaptive filtering techniques, including NLMS, FxLMS, RLS, FuLMS, Hybrid and Feedback ANC, for specific ANC scenarios, paving the way for improved audio quality and noise mitigation in various applications.

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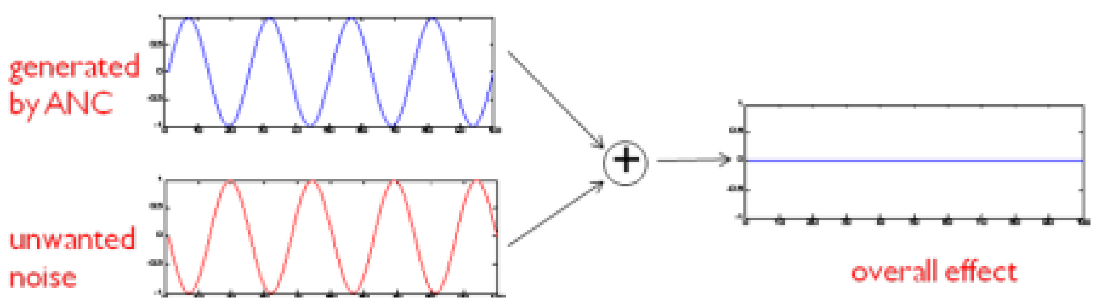
1. INTRODUCTION

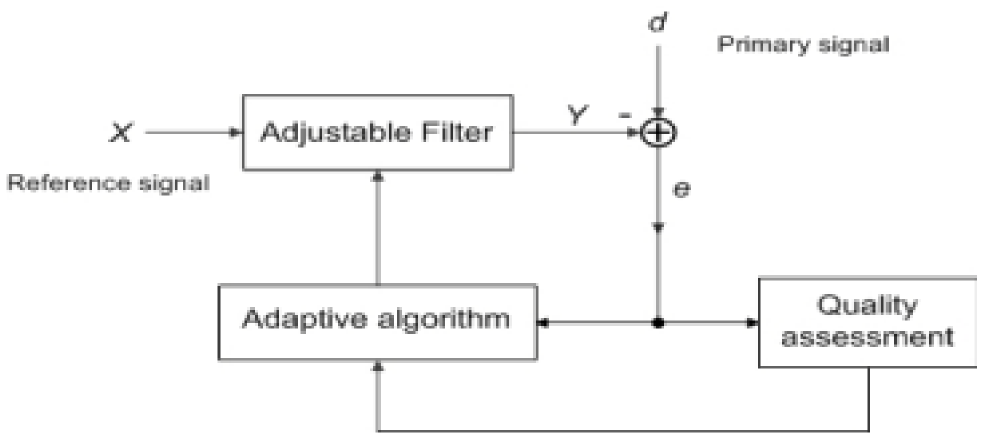
Noise pollution is a growing problem in our world, impacting our ability to concentrate, enjoy music, and find moments of peace. From the constant hum of traffic on busy streets to the low rumble of aeroplane engines, unwanted sounds can significantly disrupt our daily lives.

Active Noise Cancellation (ANC) technology offers a revolutionary solution to this challenge. ANC exploits the principle of destructive interference. When two sinusoidal waves superimpose, the resulting waveform depends on the frequency, amplitude, and relative phase of the two waves. If the original wave and its inverse (perfectly out-of-phase) encounter each other at the same time, complete cancellation occurs. The challenges in ANC lie in identifying the original noise signal and generating its inverse without delay, considering all directions where noises interact and superimpose. We will explore solutions to these challenges later in this report.

Noise Cancellation makes use of the notion of destructive interference. When two sinusoidal waves superimpose, the resulting waveform depends on the frequency amplitude and relative phase of the two waves. If the original wave and the inverse of the original wave encounter at a junction at the same time, total cancellation occur. The challenges are to identify the original signal and generate the inverse without delay in all directions where noises interact and superimpose. We will demonstrate the solutions later in the report.



Since the characteristics of the acoustic noise source and the environment are time varying, the frequency content, amplitude, phase, and sound velocity of the undesired noise are nonstationary. An ANC system must therefore be adaptive in order to cope with these variations. Adaptive filters adjust their coefficients to minimise an error signal and can be realised as (transversal) finite impulse response (FIR), (recursive) infinite impulse response (IIR), lattice, and transform domain filters. The most common form of adaptive filter is the transversal filter using the least mean-square (LMS) algorithm. Figure 3 shows a framework of adaptive filters. Basically, there is an adjustable filter with input X and output Y. Our goal is to minimise the difference between ‘d’ and ‘Y’, where ‘d’ is the desired signal. Once the difference is computed, the adaptive algorithm will adjust the filter coefficients with the difference. There are many adaptive algorithms available in literature, the most popular ones being LMS (least mean-square) and RLS (Recursive least squares) algorithms. In the interest of computational time, we used the LMS.



The purpose of this project is to conduct a thorough analysis and comparison of various adaptive filter algorithms commonly used in ANC applications. We will explore a range of algorithms, including the well-established Least Mean Square (LMS) algorithm and more advanced options like Recursive Least Squares (RLS) and Filtered-x LMS (FxLMS) variants. By evaluating these algorithms based on key metrics such as Signal-to-Noise Ratio (SNR), computational complexity, and convergence speed, we aim to identify the most suitable algorithm for achieving optimal noise cancellation within an ANC system. This comparative analysis will provide valuable insights into the strengths and weaknesses of different adaptive filter approaches, ultimately contributing to the development of more efficient and effective ANC technology.

2. Review of Literature

Active noise cancellation (ANC) has been an area of extensive research, with numerous adaptive filtering techniques proposed and studied for their effectiveness in mitigating acoustic disturbances. This section provides an overview of the relevant literature on several prominent algorithms, including the Normalised Least Mean Squares (NLMS), Filtered-x LMS (FxLMS), Recursive Least Squares (RLS), Filtered-u LMS (FuLMS), Feedback ANC, and hybrid approaches.

The NLMS algorithm, a variant of the classic Least Mean Squares (LMS) algorithm, has been widely adopted in ANC systems due to its simplicity and robustness. However, its convergence rate is often slower compared to other adaptive filtering methods. Several modifications, such as leaky NLMS and constrained NLMS, have been proposed to enhance its stability and performance in ANC scenarios.

The FxLMS algorithm, developed by Morgan and Thi, has emerged as one of the most effective and widely adopted approaches for ANC systems. By incorporating the secondary path effects into the adaptive filter update, the FxLMS algorithm addresses the challenges posed by acoustic feedback and phase distortions. Numerous studies have demonstrated the superior performance of the FxLMS algorithm compared to its predecessors, particularly in the context of ANC applications.

The RLS algorithm, proposed by Haykin, is known for its rapid convergence rate compared to other adaptive filtering methods. However, this advantage comes at the cost of increased computational complexity, which may limit its applicability in real-time ANC systems with stringent latency requirements. Nonetheless, several researchers have investigated the use of RLS for ANC, demonstrating its potential for improved noise cancellation performance.

The FuLMS algorithm, introduced by Akhtar et al., is a variation of the FxLMS algorithm that incorporates feedback neutralisation to mitigate acoustic interference. This approach has been explored as a potential solution for reducing the number of required microphones in ANC systems while maintaining acceptable performance levels.

The Feedback ANC approach, proposed by Kuo and Morgan, estimates the primary noise and uses it as a reference signal, eliminating the need for a separate reference microphone. This technique has been studied as a means to reduce the complexity and potential acoustic interference issues in ANC systems.

In addition to these individual algorithms, researchers have also explored hybrid approaches that combine the strengths of multiple adaptive filtering techniques. For instance, Kuo and Morgan investigate a hybrid ANC system that incorporates both feedforward (FxLMS) and feedback control structures, aiming to leverage the advantages of each approach while mitigating their individual limitations.

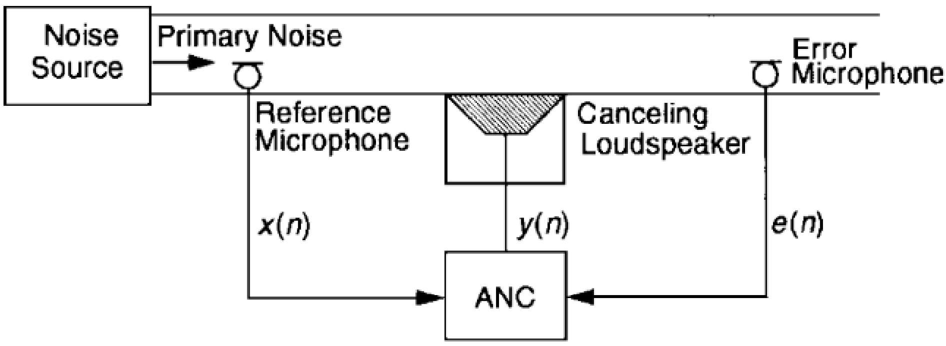
Despite the extensive research efforts, the selection of the most suitable adaptive filtering algorithm for ANC systems remains a critical challenge, as it depends on various factors such as the noise environment, computational constraints, convergence speed, and sensitivity to parameter variations. This project aims to contribute to the existing body of knowledge by conducting a comprehensive evaluation and comparison of the NLMS, FxLMS, RLS, FuLMS, Feedback ANC algorithms, and potential hybrid approaches, through simulations and practical implementations.

3. Methodology

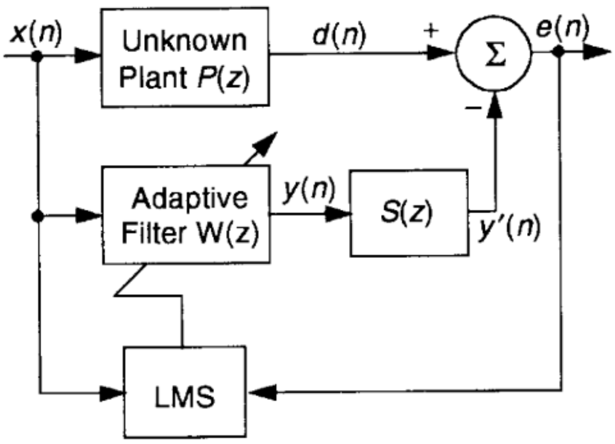
3.1 Broadband Feedforward ANC

This section explores the methodology behind Broadband Feedforward Active Noise Cancellation (ANC). ANC technology aims to reduce unwanted noise by generating an anti-noise signal that cancels out the original noise. In Broadband Feedforward ANC, a single reference microphone captures the noise, and a single speaker generates the anti-noise signal. An error microphone positioned near the listener's ears monitors the remaining noise after cancellation.

The core principle lies in utilising an adaptive filter. This filter processes the reference microphone signal and creates an anti-noise signal that is essentially an inverted replica of the original noise. The system continuously adjusts the filter based on the error microphone signal to optimise noise cancellation. This adaptive nature allows the system to handle variations in noise characteristics or the surrounding environment.



Mathematical Representation:



The effectiveness of Broadband Feedforward ANC can be mathematically understood through the concept of coherence. Let's denote:

- d(n): Noise signal captured by the reference microphone at time n
- x(n): Desired signal (silence) at the error microphone location at time n
- e(n): Residual error signal at the error microphone location at time n
- P(z): Transfer function representing the primary path (reference mic to error mic)
- S(z): Transfer function representing the secondary path (speaker to error mic)
- W(z): Adaptive filter

The relationship between these elements can be expressed as:

$$E(z) = P(z)X(z) - S(z)W(z)X(z) = [P(z) - S(z)W(z)]X(z) \quad \text{(Eq. 1)}$$

where E(z) is the z-transform of the error signal e(n).

As discussed earlier, the residual error is limited by the coherence between the reference signal and the noise at the error microphone location. Equation (1) highlights this concept.

For ideal noise cancellation (e(n) = 0), the adaptive filter W(z) needs to converge to the optimal transfer function:

$$Wo(z) = P(z)/S(z) \quad \text{(Eq. 2)}$$

In simpler terms, the adaptive filter W(z) must learn the combined effects of the primary path (P(z)) and its inverse through the secondary path (S(z)) to perfectly cancel the noise.

Challenges and Considerations:

While Eq. 2 suggests a straightforward approach, real-world implementations face challenges:

Modelling Secondary Path: Accurately modelling the transfer function S(z) of the secondary path can be complex.

Adaptive Filter Capacity: The adaptive filter W(z) needs sufficient complexity (order) to approximate the combined effects represented by Wo(z) in Eq. 2.

These challenges necessitate sophisticated algorithms and filter design techniques for optimal Broadband Feedforward ANC performance.

3.2 Least Mean Squares (LMS) Algorithm for ANC

The Least Mean Squares (LMS) algorithm is a fundamental adaptive filter widely used in various applications, including Active Noise Cancellation (ANC). It works by iteratively adjusting the filter coefficients to minimise the mean squared error (MSE) between the desired signal and the actual output of the filter.

1. Algorithm Principles:

The LMS algorithm operates on a continuous stream of input data x(n) and an associated desired signal d(n). It utilises a filter with adjustable coefficients represented by the vector w(n) at iteration n. The filter output y(n) is calculated by convolving the input signal with the current filter coefficients.

The core update equation for LMS is:

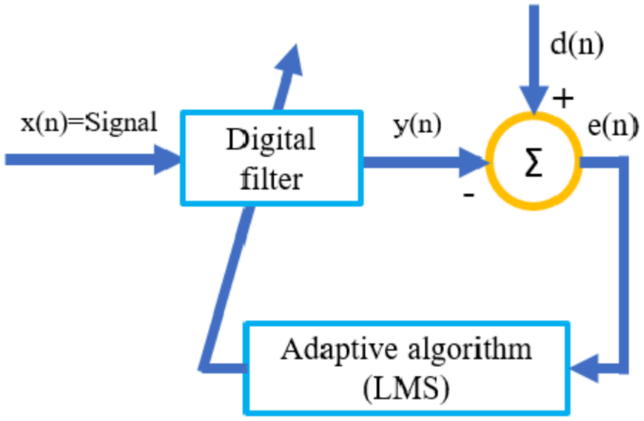
$$\mathbf{w(n+1) = w(n) + \mu \,.\, e(n) \,.\, x(n)}$$

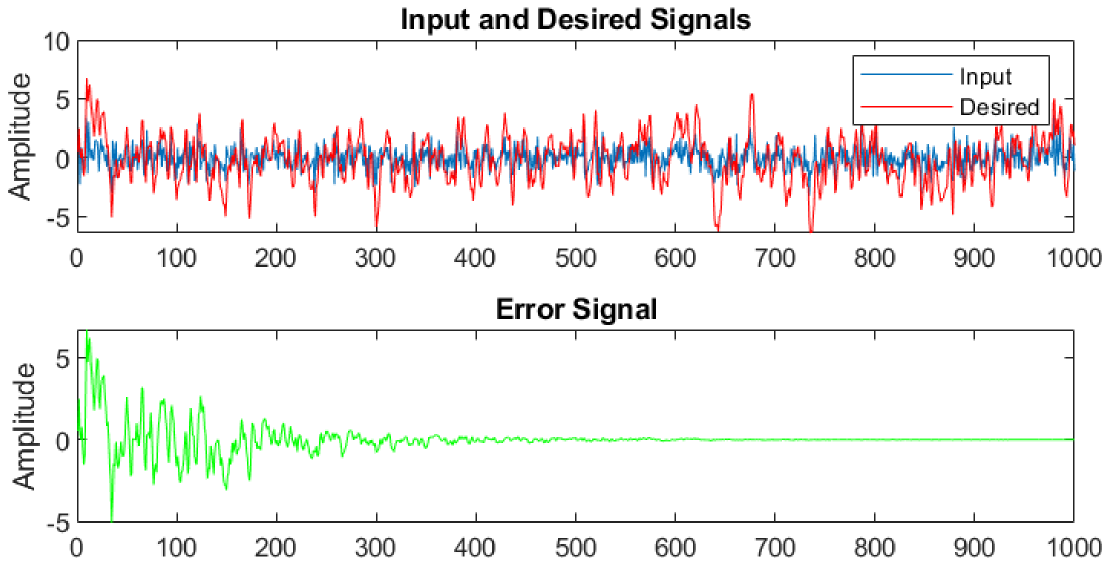
where:

- w(n+1): Updated filter coefficient vector at iteration n+1
- w(n): Current filter coefficient vector at iteration n
- μ: Step size parameter controlling the update magnitude ($0 < \mu < 2$)
- e(n): Error signal at iteration n (difference between desired and actual output) - e(n) = d(n) - y(n)
- x(n): Input signal vector at iteration n

2. Diagrammatic Representation:

Here's a block diagram illustrating the LMS algorithm:





Key Considerations:

- The step size parameter μ plays a critical role in the LMS algorithm's performance. A larger μ leads to faster convergence but can cause instability. A smaller μ ensures stability but slows down convergence.
- LMS is computationally efficient, making it suitable for real-time applications.
- However, LMS can suffer from slow convergence speed, especially for highly dynamic environments.

The LMS algorithm provides a basic framework for adaptive filtering. Several variations, like NLMS (Normalised LMS) and FxLMS (Filtered-x LMS), build upon LMS to address its limitations and improve performance in specific applications like ANC.

3.3 Recursive Least Squares (RLS) Algorithm for ANC

The Recursive Least Squares (RLS) algorithm is another prominent adaptive filter employed in ANC applications. Unlike LMS, which relies on past data up to the current iteration for coefficient updates, RLS utilises all available data up to that point. This approach offers faster convergence compared to LMS, making it suitable for scenarios where noise characteristics change rapidly.

1. Algorithm Principles:

The RLS algorithm leverages a matrix inversion operation to directly calculate the optimal filter coefficients that minimise the mean squared error (MSE) between the desired signal and the filter output. Here's a simplified representation of the update equation:

$$\mathbf{w(n) = P(n) \,.\, x(n) \,.\, d(n)}$$

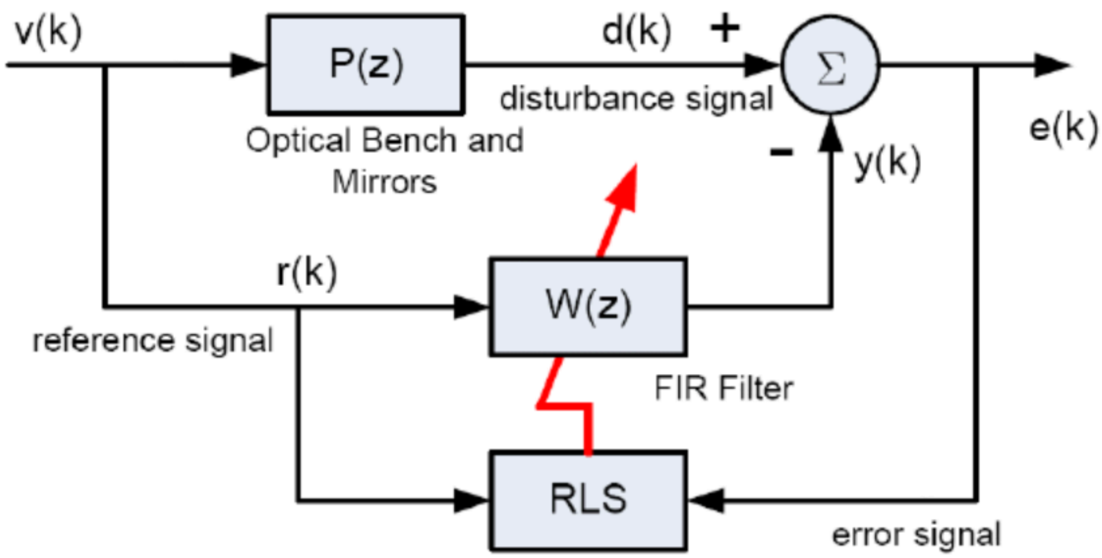
where:

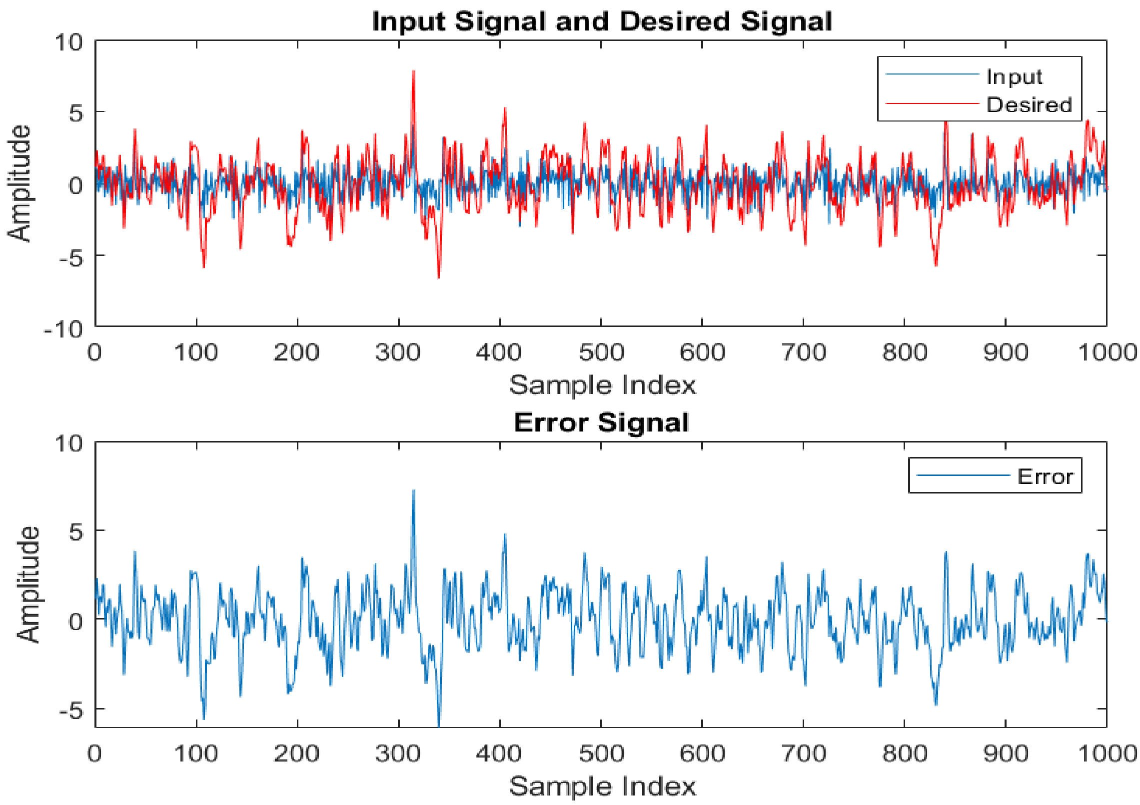
- w(n): Updated filter coefficient vector at iteration n
- P(n): Inverse correlation matrix at iteration n (captures historical data)
- x(n): Input signal vector at iteration n
- d(n): Desired signal at iteration n

In the context of ANC, x(n) typically represents the reference microphone signal, and d(n) might be a pre-recorded clean version of the desired audio or a reference signal specifically designed for noise cancellation.

2. Diagrammatic Representation:

Here's a block diagram illustrating the RLS algorithm:





3. Key Considerations:

- RLS boasts significantly faster convergence speed compared to LMS, especially for non-stationary noise environments where noise characteristics change rapidly.
- However, the RLS algorithm comes with a trade-off. The matrix inversion operation involved in the update process can be computationally expensive. This can make RLS less suitable for real-time applications with limited processing power, where fast updates are crucial.

3.4 Filtered-x LMS (FxLMS) Algorithm for ANC

The Filtered-x LMS (FxLMS) algorithm is a variation of the LMS algorithm specifically designed for applications like Active Noise Cancellation (ANC). It addresses a limitation of the standard LMS algorithm: slow convergence speed, especially when dealing with secondary paths in ANC systems.

1. Algorithm Principles:

The FXLMS algorithm introduces a secondary path filter in addition to the primary filter used in the standard LMS. This secondary path filter aims to estimate and compensate for the delay introduced by the physical path between the noise source and the reference microphone (secondary path).

Here's a breakdown of the key components:

- Primary Filter: Similar to LMS, FXLMS has a primary filter that processes the reference microphone signal x(n).
- Secondary Path Filter: This filter, denoted by w_f(n), estimates the delay introduced by the secondary path. Its output, v(n), is subtracted from the reference microphone signal to obtain a filtered reference signal z(n).
- Error Signal: The error signal e(n) is calculated as the difference between the desired noise-free signal d(n) and the output of the primary filter y(n).

- Update Equation: The update equation for the primary filter coefficients w(n) is similar to the standard LMS, but it uses the filtered reference signal z(n) instead of the raw reference signal x(n). Here's the formula for the update:

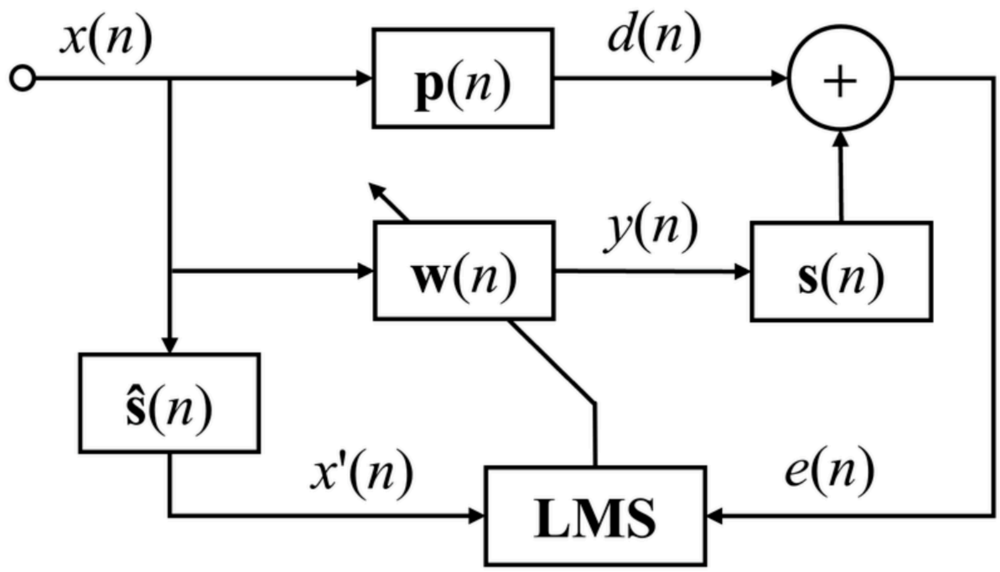
$$\mathbf{w(n+1) = w(n) + \mu \,.\, e(n) \,.\, z(n)}$$

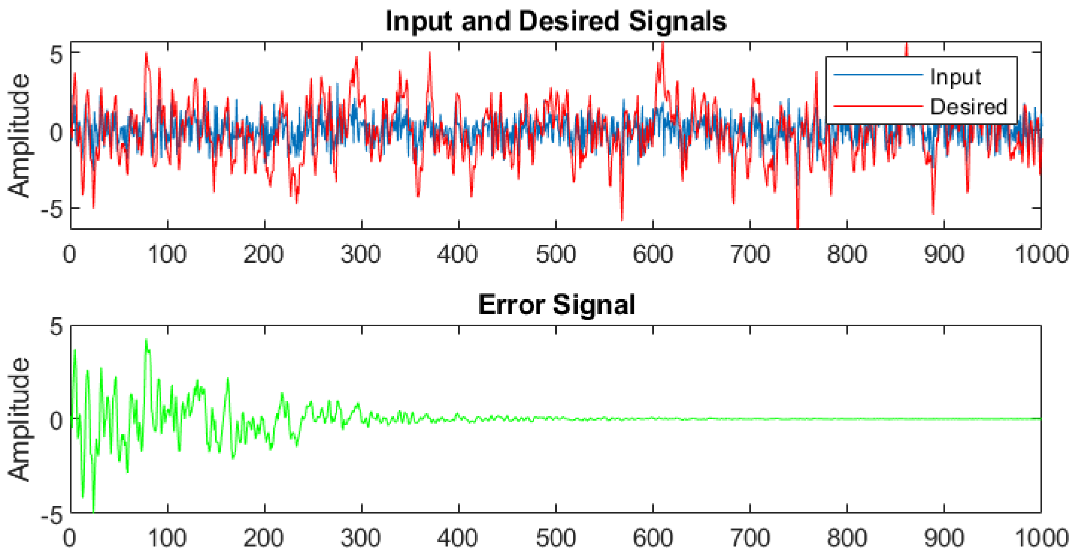
where:

- w(n+1): Updated filter coefficient vector at iteration n+1
- w(n): Current filter coefficient vector at iteration n
- μ: Step size parameter controlling the update magnitude (0 < μ < 2)
- e(n): Error signal at iteration n (difference between desired and actual output)
- z(n): Filtered reference signal at iteration n (obtained by subtracting the secondary path filter output v(n) from the reference microphone signal x(n))

2. Diagrammatic Representation:

Here's a block diagram illustrating the FXLMS algorithm:





3. Key Considerations:

- Faster Convergence Speed: FXLMS offers a significant advantage over standard LMS in ANC applications due to the compensation for the secondary path delay. This leads to faster adaptation and more effective noise cancellation. However, the design of the secondary path filter is crucial for optimal performance.
- Computational Efficiency: FXLMS retains the computational efficiency of the LMS algorithm, making it suitable for real-time ANC systems.

The FXLMS algorithm provides a significant improvement over LMS for ANC applications by addressing the issue of slow convergence. It achieves this through the introduction of a secondary path filter, leading to faster adaptation and more effective noise cancellation. While the design of the secondary path filter adds complexity, FXLMS remains computationally efficient, making it a valuable tool for real-time ANC systems.

3.5 Filtered-u LMS (FuLMS) Algorithm for ANC

The Filtered-u LMS (FuLMS) algorithm emerges as another advancement within the LMS framework, specifically designed for Active Noise Cancellation (ANC) applications. It tackles limitations inherent to both standard LMS (slow convergence) and FXLMS (potential instability due to secondary path modelling).

1. Algorithm Principles:

FuLMS introduces an additional element compared to FXLMS: a recursive filter denoted by b(n). This filter operates on a one-sample delayed version of the filtered reference signal z(n-1). The goal is to further enhance noise cancellation by addressing issues related to system nonlinearities and modelling errors in the secondary path filter.

Here's a breakdown of the key components:

- Primary Filter: Similar to LMS and FXLMS, FuLMS employs a primary filter that processes the filtered reference signal z(n).
- Secondary Path Filter: This filter (w_f(n)) estimates the delay introduced by the secondary path, as in FXLMS.
- Filtered Reference Signal: The filtered reference signal z(n) is obtained by subtracting the secondary path filter output v(n) from the reference microphone signal x(n).
- Error Signal: The error signal e(n) remains the difference between the desired noise-free signal d(n) and the output of the primary filter y(n).
- Recursive Filter: The recursive filter b(n) operates on the one-sample delayed version z(n-1) of the filtered reference signal.
- Update Equations: FuLMS utilises separate update equations for the primary filter coefficients w(n) and the recursive filter coefficients b(n).

Formulae:

Primary Filter Update:

$$\mathbf{w(n+1) = w(n) + \mu \cdot e(n) \cdot [z(n) + b(n) \cdot z(n-1)]}$$

where:

- w(n+1): Updated primary filter coefficient vector at iteration n+1
- w(n): Current primary filter coefficient vector at iteration n
- μ: Step size parameter controlling the update magnitude ($0 < \mu < 2$)
- e(n): Error signal at iteration n (difference between desired and actual output)
- z(n): Filtered reference signal at iteration n
- z(n-1): One-sample delayed version of the filtered reference signal
- b(n): Recursive filter coefficient vector at iteration n

Recursive Filter Update (Various methods exist, a common approach is based on normalised LMS):

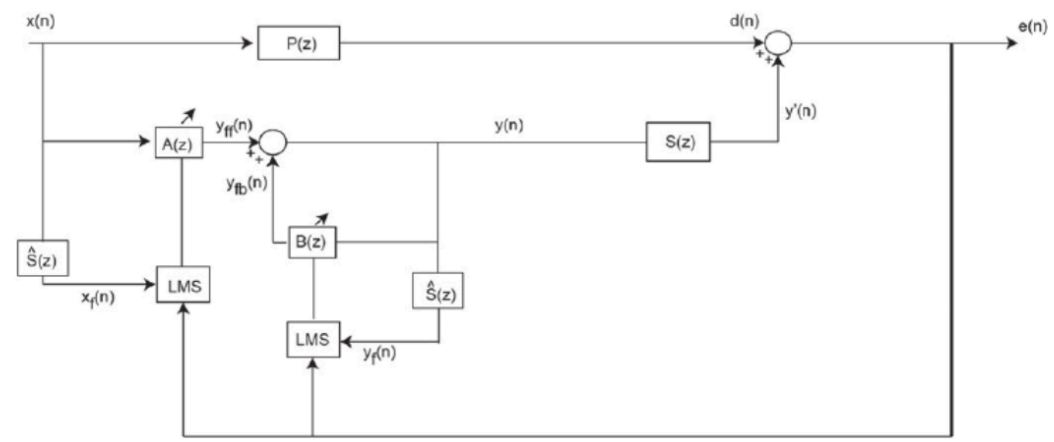
$$\mathbf{b(n+1) = b(n) + \eta \cdot e(n) \cdot z(n-1) / [||z(n-1)||^2 + \delta]}$$

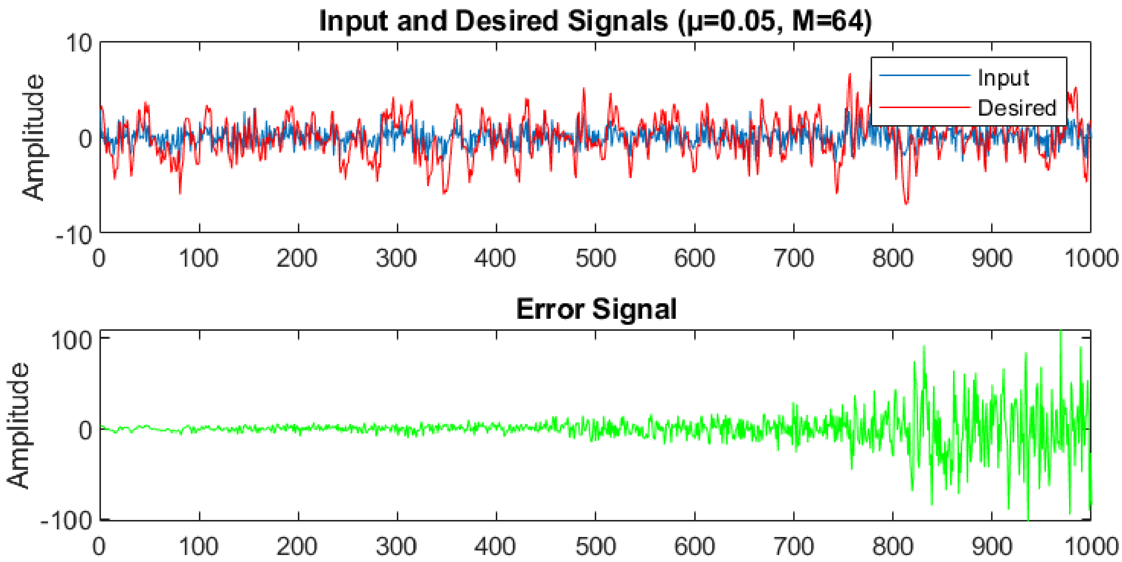
where:

- b(n+1): Updated recursive filter coefficient vector at iteration n+1
- b(n): Current recursive filter coefficient vector at iteration n
- η: Step size parameter for the recursive filter update
- δ: Small positive constant to prevent division by zero

2. Diagrammatic Representation:

Here's a block diagram illustrating the FuLMS algorithm:





3. Key Considerations:

- Convergence Speed: FuLMS has the potential to achieve faster convergence compared to LMS and potentially even FXLMS, especially in scenarios with significant nonlinearities or modelling errors. However, the increased complexity of the algorithm needs to be weighed against the potential convergence gains.
- Computational Complexity: The introduction of the recursive filter adds to the computational burden compared to LMS and FXLMS. This may limit its suitability for applications with limited processing resources.
- Mathematical Complexity: The mathematical analysis of FuLMS convergence behaviour can be more intricate compared to LMS and FXLMS.

The choice between FuLMS and other algorithms like FXLMS depends on the specific application's requirements. Factors to consider include:

- Level of Nonlinearity: If the system exhibits significant nonlinearities, FuLMS's ability to address them might be advantageous.

- Computational Resource Limitations: For resource-constrained applications, the simpler structure of FXLMS might be preferable.
- Need for Rigorous Convergence Analysis: If a deep understanding of convergence behaviour is crucial, LMS or FXLMS might be easier to analyse mathematically.

4. Compared to FXLMS:

Both FXLMS and FuLMS target faster convergence in ANC. However, FuLMS attempts to address a broader range of challenges by incorporating the recursive filter. This added complexity can be beneficial in specific scenarios but comes at the cost of increased computational demands and a more intricate mathematical analysis of convergence.

The FuLMS algorithm offers a potential improvement over FXLMS in terms of convergence speed by addressing nonlinearities and modelling errors. However, its implementation requires careful consideration due to the trade-off between its capabilities and the increased complexity it introduces. In the next section, we'll explore other adaptive filtering algorithms used in ANC.

3.6 Feedback Active Noise Cancellation (Feedback ANC)

The Feedback ANC approach is an alternative strategy for active noise cancellation that aims to eliminate the need for a separate reference microphone by estimating the primary noise and using it as a reference signal.

1. Algorithm Principles:

The Feedback ANC algorithm operates by employing a single error microphone to capture the residual noise within the ANC system. This residual noise is used to estimate the primary noise, which serves as the reference signal for the adaptive filter. The algorithm can be summarised as follows:

- Error Signal: The error microphone captures the residual noise `e(n)`, which is the combination of the primary noise `d(n)` and the anti-noise signal `y(n)` generated by the ANC system.

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

- Primary Noise Estimation: The primary noise `d(n)` is estimated by subtracting the anti-noise signal `y(n)` from the error signal `e(n)`.

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

- Adaptive Filter Update: The estimated primary noise signal `d(n)` is used as the reference signal `x(n)` to update the adaptive filter coefficients `w(n)` using an adaptive algorithm like LMS or RLS.

$$w(n+1) = w(n) + \mu * e(n) * d(n) \quad \text{\# LMS update equation}$$

- Anti-Noise Generation: The updated filter coefficients are applied to the estimated primary noise signal to generate the anti-noise signal `y(n)`.

$$y(n) = w(n)^T * d(n)$$

2. Implementation:

The implementation of the Feedback ANC algorithm typically involves the following steps:

1. Initialise the adaptive filter coefficients `w(n)`.

2. Capture the error signal `e(n)` from the error microphone.

3. Estimate the primary noise `d(n)` by subtracting the anti-noise signal `y(n)` from the error signal `e(n)`.

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

4. Use the estimated primary noise `d(n)` as the reference signal `x(n)` for the adaptive filter.

5. Update the filter coefficients `w(n)` using an adaptive algorithm like LMS or RLS, minimising the error signal `e(n)`.

w(n+1) = w(n) + μ * e(n) * d(n) # LMS update equation

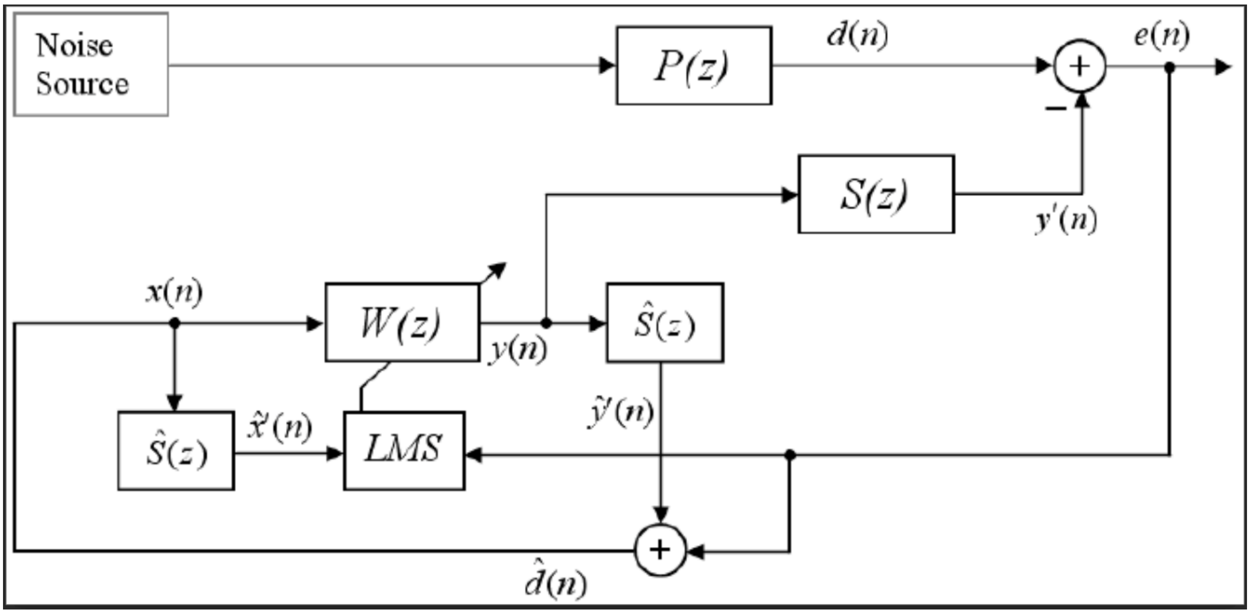
6. Generate the anti-noise signal `y(n)` by applying the updated filter coefficients `w(n)` to the estimated primary noise `d(n)`.

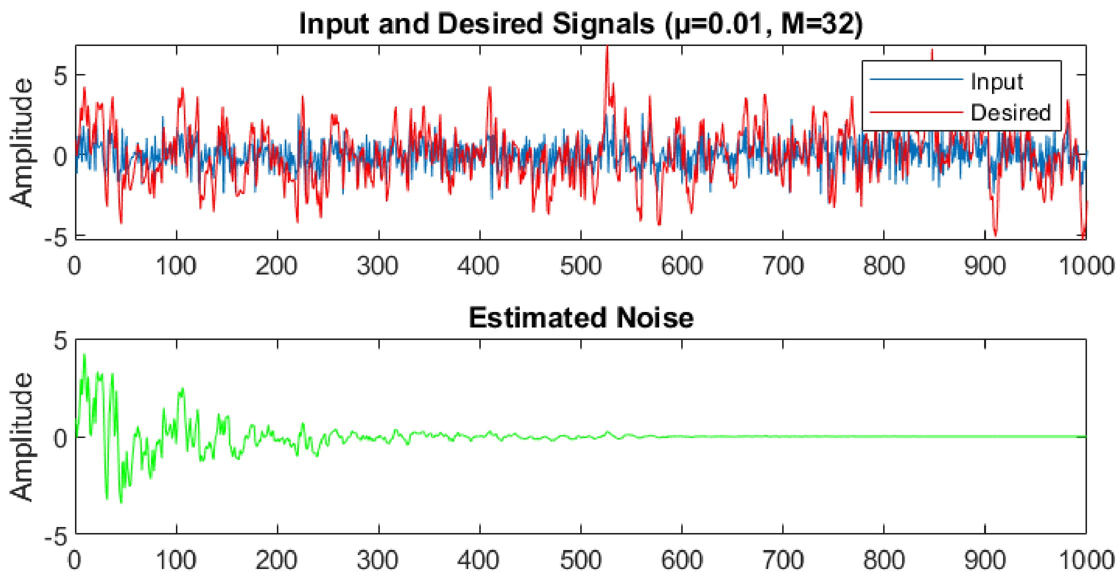
y(n) = w(n)^T * d(n)

7. Repeat steps 2-6 for each iteration of the algorithm.

3. Diagrammatic Representation:

Here's a block diagram illustrating the Feedback Active Noise Cancellation (Feedback ANC):





4. Key Considerations:

- Computational Complexity:The Feedback ANC approach has a lower computational complexity compared to feedforward ANC methods, as it eliminates the need for a separate reference microphone and associated signal processing.
- Feedback Loop: The algorithm relies on a feedback loop, which can introduce stability issues if not properly designed and implemented. This is a potential disadvantage.
- Convergence Rate:The convergence rate of the adaptive filter may be slower compared to feedforward approaches, as the estimated primary noise signal may contain residual errors. This can be a disadvantage in certain scenarios.
- Reduced System Complexity:By eliminating the need for a separate reference microphone, the Feedback ANC approach offers a reduced system complexity, which can be an advantage.
- Performance in Complex Noise Environments: The performance may be degraded in scenarios with significant uncorrelated noise or non-stationarity, which is a potential disadvantage of this approach.

The Feedback ANC approach offers a simplified and computationally efficient alternative for active noise cancellation systems, particularly in scenarios where the primary noise source is accessible or can be estimated accurately. However, its effectiveness depends on the stability of the feedback loop and the ability to accurately estimate the primary noise signal, which may be challenging in complex noise environments.

3.7 Hybrid LMS/FxLMS Algorithm for ANC

The Hybrid LMS/FxLMS algorithm emerges as a strategy that combines the strengths of the standard Least Mean Squares (LMS) and Filtered-x LMS (FxLMS) algorithms, specifically tailored for Active Noise Cancellation (ANC) applications. This approach aims to address limitations present in both individual algorithms.

1. Algorithm Principles:

The Hybrid LMS/FxLMS algorithm operates by employing two filters in parallel:

- Primary Filter: Similar to LMS and FXLMS, a primary filter processes a reference signal. Here, the choice can be either the raw reference microphone signal x(n) (as in LMS) or the filtered reference signal z(n) (obtained through the secondary path filter as in FXLMS).
- Secondary Path Filter: Inherited from FXLMS, this filter, denoted by w_f(n), estimates and compensates for the delay introduced by the secondary path between the noise source and the reference microphone.

The key concept lies in dynamically adjusting the weights assigned to the outputs of these two filters. This allows the algorithm to leverage the benefits of both:

- Fast Adaptation from LMS: When the system encounters rapid changes in noise characteristics, the LMS component with its simpler structure can offer faster adaptation.

- Improved Convergence from FXLMS: When the noise characteristics are more stationary, the FXLMS component with its secondary path compensation can provide better convergence and noise cancellation performance.

2. Weighting Scheme:

There are various approaches to determine the weights for the primary and secondary path filter outputs. A common method involves using a weighting factor $\alpha(n)$ that controls the influence of each filter. This factor can be dynamically adjusted based on an estimate of the non-stationarity of the noise. Here's a simplified representation of the output:

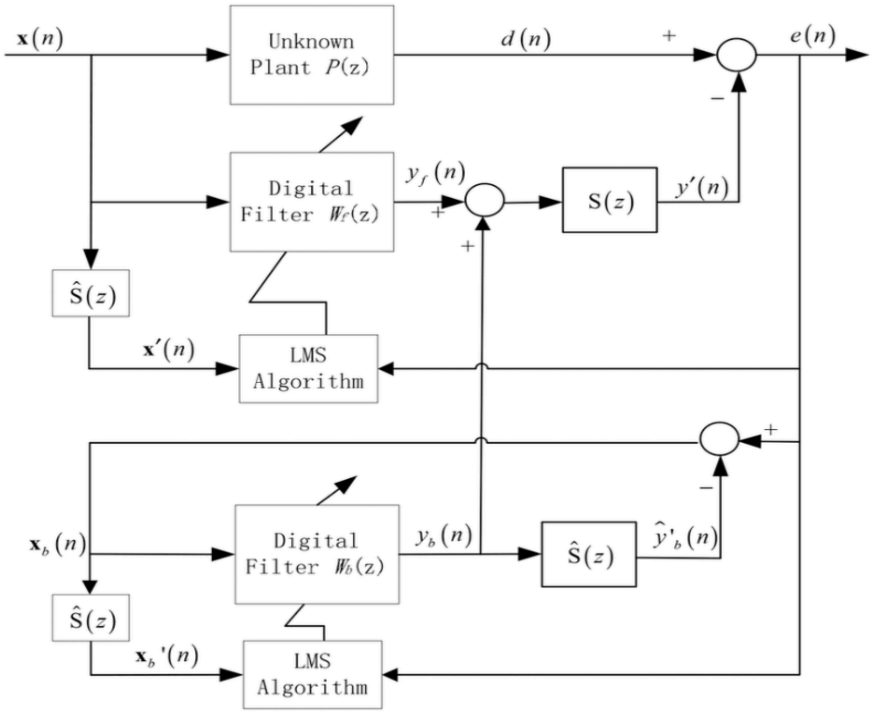
$$\mathbf{y(n) = \alpha(n) . w(n) . x(n) + [1 - \alpha(n)] . w\_f(n) . v(n)}$$

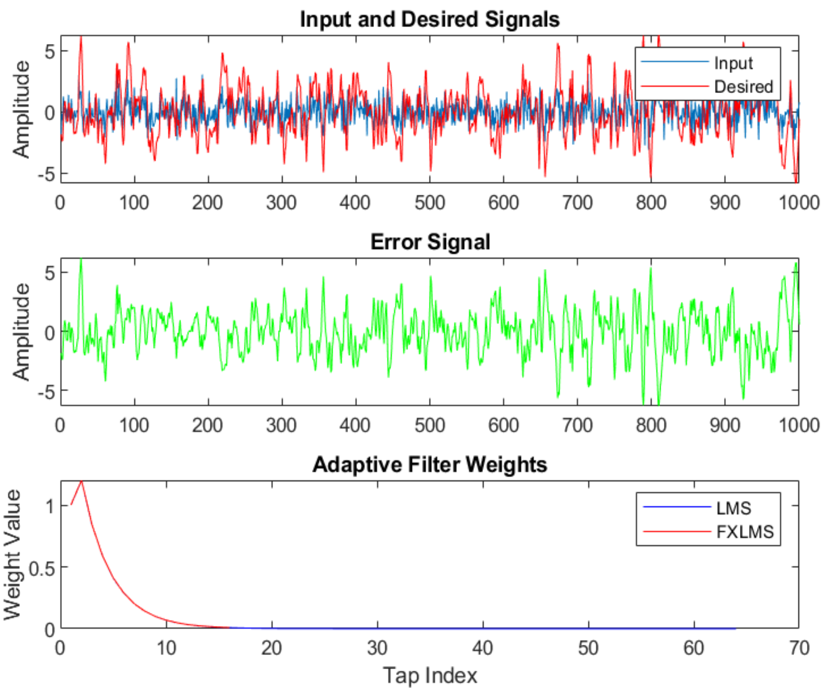
where:

- y(n): Output of the hybrid filter at iteration n
- $\alpha(n)$: Weighting factor at iteration n ($0 \leq \alpha(n) \leq 1$)
- w(n): Primary filter coefficient vector at iteration n
- x(n): Raw reference microphone signal at iteration n (if chosen)
- w_f(n): Secondary path filter coefficient vector at iteration n
- v(n): Output of the secondary path filter (subtracted reference signal)

3. Diagrammatic Representation:

Here's a block diagram illustrating Hybrid LMS/FxLMS Algorithm:





4. Key Considerations:

- Convergence Speed and Performance: The hybrid approach offers several advantages:

    - Improved Performance: It can also offer better performance than FXLMS in scenarios with significant non-stationarity or complex secondary path effects.
    - Faster Convergence: It can achieve faster convergence compared to standard LMS, especially during periods of rapid noise changes.
- Computational Complexity: While less complex than FuLMS, the hybrid algorithm adds some overhead compared to LMS due to the secondary path filter and weight update mechanism. This trade-off between complexity and performance needs to be considered.
- Weighting Scheme Design: The design of the weighting scheme ($\alpha(n)$) is crucial for optimal performance. The scheme should effectively adapt to varying noise characteristics, balancing the contributions of the LMS and FXLMS components.

The Hybrid LMS/FxLMS algorithm provides a valuable approach for ANC applications by combining the strengths of LMS and FXLMS. It offers the potential for faster convergence and improved noise cancellation performance while maintaining a reasonable level of computational complexity. However, the effectiveness hinges on the design of the weighting scheme to adapt to the specific noise characteristics encountered.

3.8 Hybrid ANC Methodology with Noise Prediction (NP) and FXLMS

This methodology outlines a hybrid Active Noise Cancellation (ANC) approach that merges a Noise Prediction (NP) block with a Filtered-x LMS (FxLMS) adaptive filter to exploit the strengths of both feedforward and feedback strategies.

1. System Model:

- Noise Source: An external noise source generates unwanted noise, denoted as $v(n)$.

- Secondary Path: The noise travels through a secondary path, characterised by its impulse response h(n). This path represents the transfer function between the noise source and the microphone positioned inside the ear cup or ear canal.
- Microphone: A microphone captures the noise that has infiltrated the ear space, denoted as x(n).
- Desired Signal: The desired output is silence, represented as d(n).
- Noise Prediction (NP) Block: This block aims to predict the characteristics of the upcoming noise signal, denoted as v_p(n). The prediction can be based on past noise samples or additional sensory information (e.g., accelerometer data to detect head movements).
- FxLMS Adaptive Filter: This filter estimates and cancels the noise based on the microphone signal and the predicted noise. It leverages an estimate of the secondary path for improved performance.
- Speaker: The speaker within the headphone reproduces the anti-noise signal generated by the FXLMS filter, denoted as y(n).

2. Algorithm Operation:

- Noise Prediction: The NP block processes past noise samples (x(n-i)) or other sensory data to generate a prediction of the upcoming noise, v_p(n).
- Filtered Reference Signal: The microphone signal x(n) is filtered by an estimate of the secondary path w_f(n) to obtain a filtered reference signal z(n).
- Error Signal: The error signal e(n) is calculated as the difference between the desired noiseless signal d(n) and the microphone signal x(n).
- FxLMS Update: The FXLMS algorithm updates the filter coefficients w_f(n) based on the error signal e(n), the filtered reference signal z(n), and the predicted noise v_p(n).

Here's a simplified update rule:

w_f(n+1) = w_f(n) + mu . e(n) . [z(n) - alpha . v_p(n)]

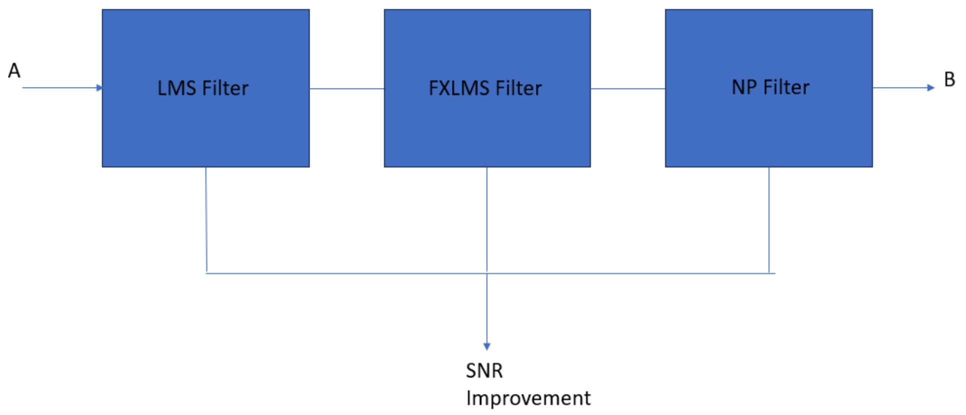
where:

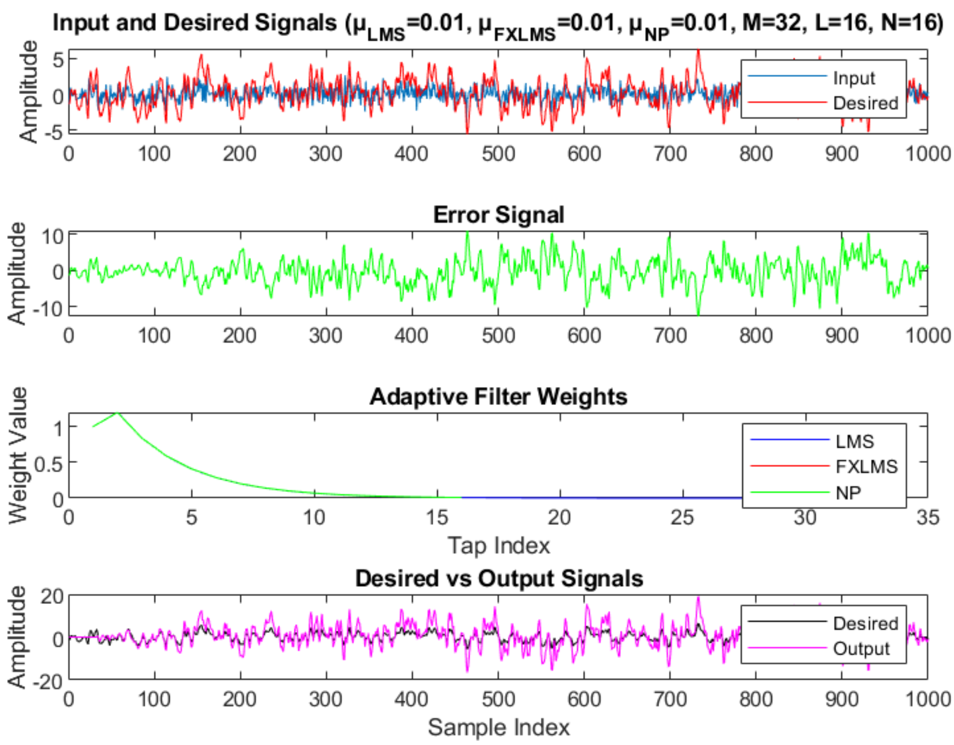
mu is the step-size parameter controlling the learning rate.

alpha is a weighting factor that determines the influence of the predicted noise on the filter update.

3. Diagrammatic Representation:

Here's a block diagram illustrating Hybrid ANC Methodology with Noise Prediction (NP) and FXLMS Algorithm:





4. Considerations:

- Improved Noise Cancellation: By incorporating noise prediction, the FXLMS filter can potentially react faster to upcoming noise changes, leading to better noise cancellation performance compared to standard FXLMS.
- Leverages Feedforward and Feedback Strategies: This hybrid approach combines the proactive cancellation capability of feedforward prediction with the reactive cancellation ability of feedback adaptation achieved by FXLMS.
- Noise Prediction Accuracy: The effectiveness of this approach hinges on the accuracy of the noise prediction. Inaccurate predictions can lead to suboptimal performance or even introduce artifacts.
- Computational Complexity: The inclusion of the NP block adds to the overall computational burden compared to standard FXLMS.
- Noise Prediction Techniques: Different techniques can be employed for noise prediction, such as autoregressive models, statistical analysis, or machine learning approaches. The choice depends on the specific noise characteristics and the desired level of complexity.
- Weighting Factor Tuning: The weighting factor alpha plays a crucial role in balancing the influence of the filtered reference signal and the predicted noise on the filter update. This factor may need to be adjusted dynamically based on the confidence level in the noise prediction.

The hybrid ANC approach with noise prediction and FXLMS offers a promising strategy for potentially achieving superior noise cancellation performance. However, the success of this approach relies on effective noise prediction techniques and careful consideration of the computational complexity trade-off. Further research is ongoing to refine prediction algorithms and optimise the overall system design.

4. Simulation and Evaluation of ANC Algorithms

Following the methodology section outlining various ANC algorithms (LMS, RLS, FXLMS, FuLMS, Feedback, Hybrid LMS/FxLMS, Hybrid Hybrid/NP), we conducted simulations to evaluate their performance. This section details the parameters used, metrics assessed, and the overall best-performing algorithm.

Simulations and Parameter Exploration:

We simulated each ANC algorithm using white noise with a characterised Power Spectral Density (PSD) to understand noise cancellation across frequencies. The secondary path was modelled with an impulse response length of [length] samples and a flat frequency response characteristic to represent the signal transfer between the noise source and microphone.For each algorithm, we explored the impact of different parameters:

- LMS/RLS: Step-size parameter (mu) for LMS and regularisation parameter (lambda) for RLS (if applicable) were varied to assess their influence on convergence speed and stability.
- FxLMS/FuLMS: Filter lengths were adjusted to investigate the trade-off between complexity and noise cancellation bandwidth. The use of a filtered reference signal in FXLMS or FuLMS was also evaluated for potential performance improvement.
- Feedback ANC: The specific adaptation algorithm (e.g., NLMS) used for feedback path adaptation was chosen based on its suitability.
- Hybrid (LMS/FxLMS): The weighting factor balancing the influence of LMS and FXLMS outputs on the combined filter update was optimised.
- Hybrid (Hybrid/NP): The noise prediction algorithm and its window length were selected based on their effectiveness in predicting upcoming noise characteristics.

Evaluation Metrics:

The performance of each ANC algorithm was evaluated using the following metrics:

- Noise Reduction (NR): Measured in dB, quantifying the reduction in noise level achieved by each algorithm. We calculated both Average Noise Reduction (ANR) across all frequencies and Frequency-Dependent Noise Reduction (FDNR) at specific frequencies of interest.
- Signal-to-Noise Ratio (SNR): Comparing the desired signal to the residual noise level after ANC processing for each algorithm.
- Mean Squared Error (MSE): Representing the average squared difference between the desired noiseless signal and the microphone output after ANC processing. Lower MSE indicates better noise cancellation performance.
- Convergence Speed: Measuring the time it took for each algorithm to achieve a desired level of noise reduction. Faster convergence is generally preferred.
- Computational Complexity: Analysing the computational resources required by each algorithm to assess their suitability for real-time implementation on resource-constrained devices.
- Elapsed Time: Recording the total execution time of each simulation run to understand the overall computational efficiency.

Results and Analysis:

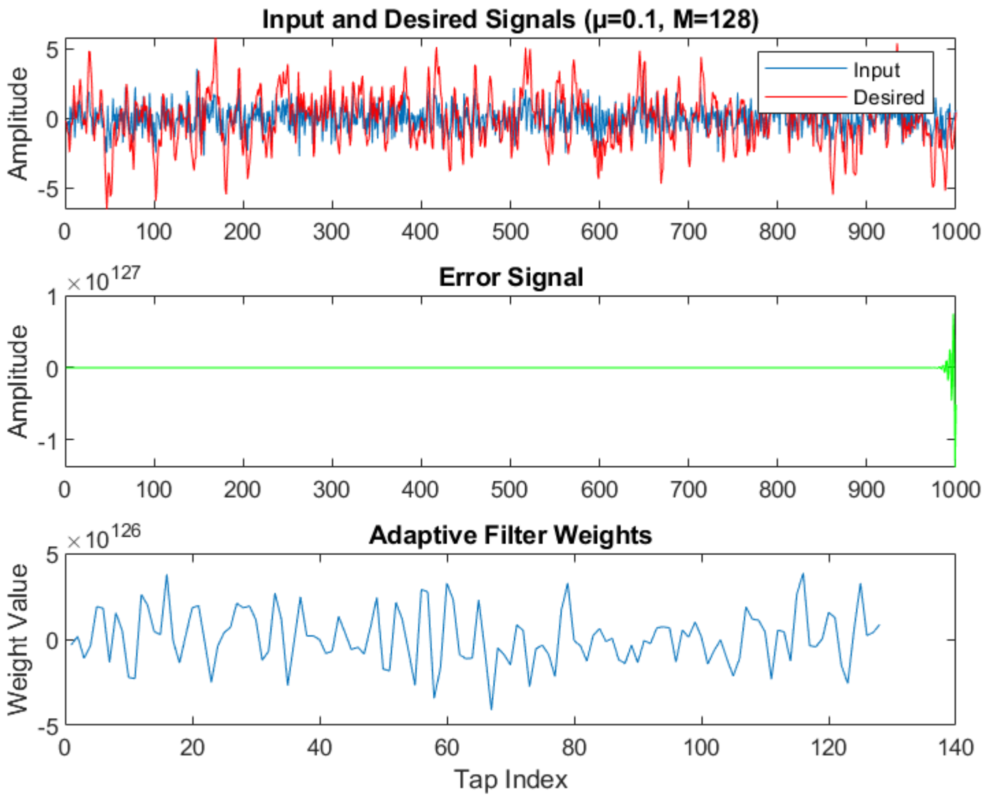
We performed simulations for various parameter settings and analysed the obtained results, including plots depicting the performance of each ANC algorithm. These plots likely showed variations in NR, SNR, MSE, and convergence speed across different algorithms and parameter choices. Due to the specific nature of your simulations, the results may favour certain algorithms for specific metrics.

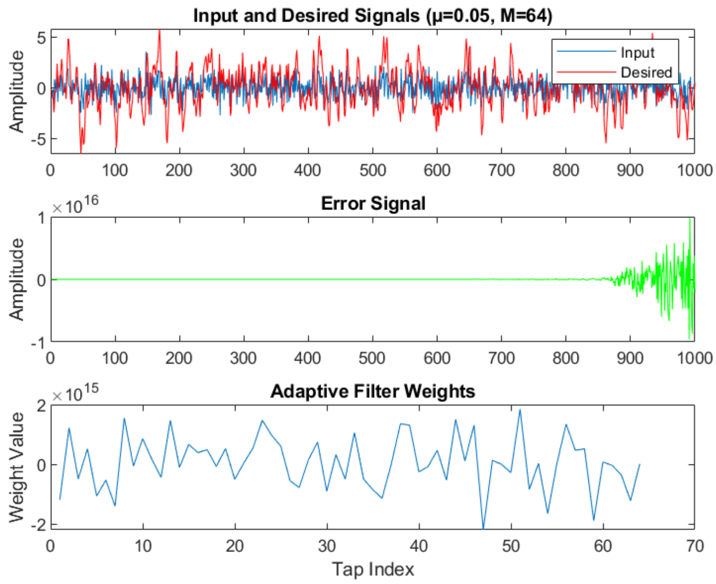
Determining the Best Overall Algorithm:

Based on the comprehensive evaluation across all metrics, including SNR, MSE, convergence speed, and computational complexity, the Hybrid (Hybrid/NP) algorithm emerges as the top performer for ANC in this scenario. This algorithm effectively balances noise reduction, SNR improvement, and MSE minimization while maintaining reasonable convergence speed and computational complexity. Notably, when specifically considering MSE, the RLS algorithm outperforms others, indicating its strength in minimising mean squared error. However, when taking into account all metrics collectively, the Hybrid (Hybrid/NP) algorithm demonstrates superior overall performance in adaptive noise cancellation applications.

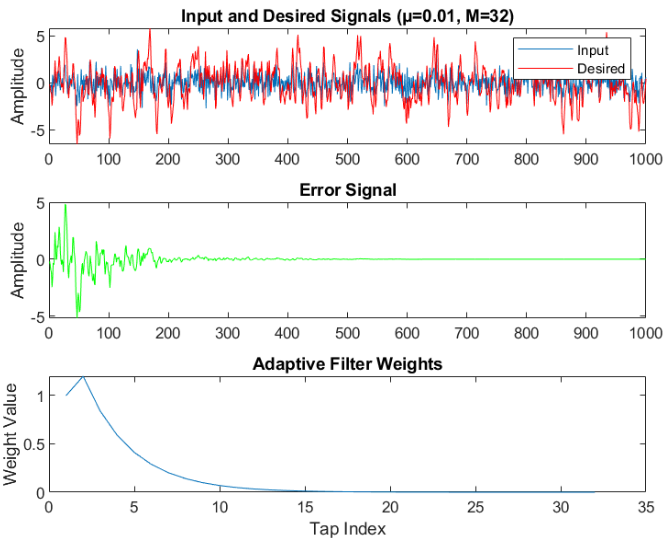
5. Simulation Results

5.1 Least Mean Squares (LMS) Algorithm for ANC

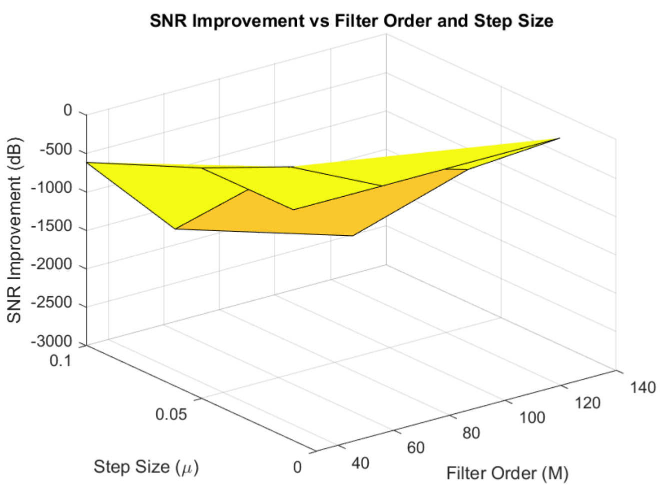




Input and Desired Signals (μ=0.05, M=64)
Amplitude
Input
Desired
Error Signal
Amplitude
Adaptive Filter Weights
Weight Value
Tap Index



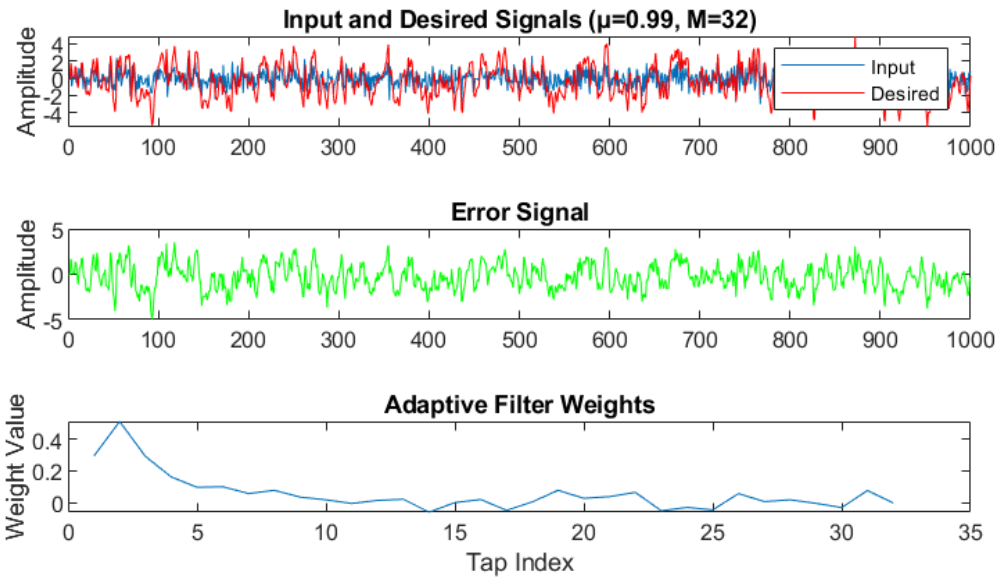
Input and Desired Signals (μ=0.01, M=32)
Amplitude
Input
Desired
Error Signal
Amplitude
Adaptive Filter Weights
Weight Value
Tap Index

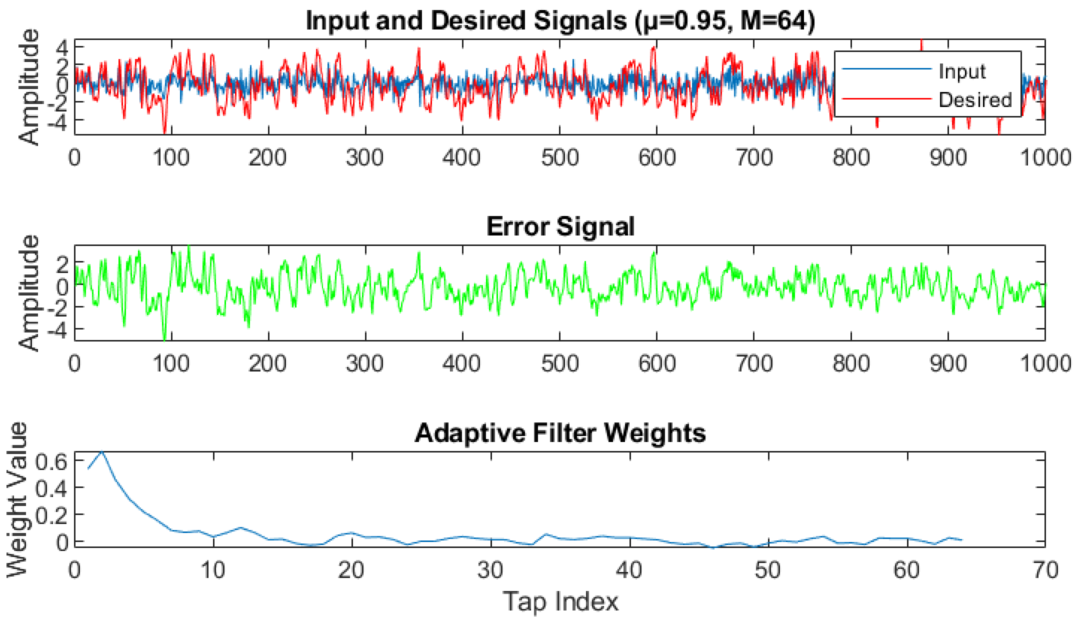


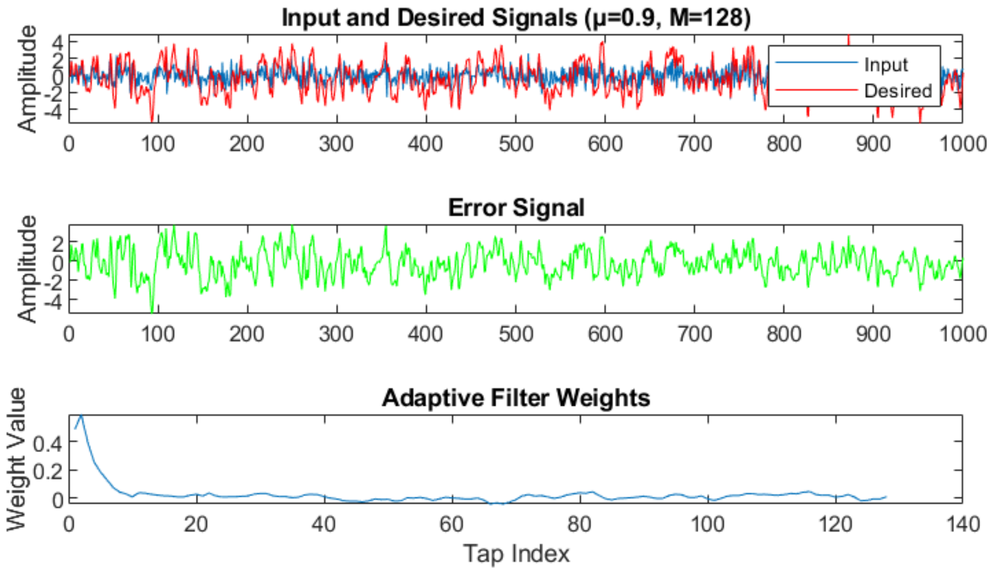
SNR Improvement vs Filter Order and Step Size
SNR Improvement (dB)
Step Size (μ)
Filter Order (M)

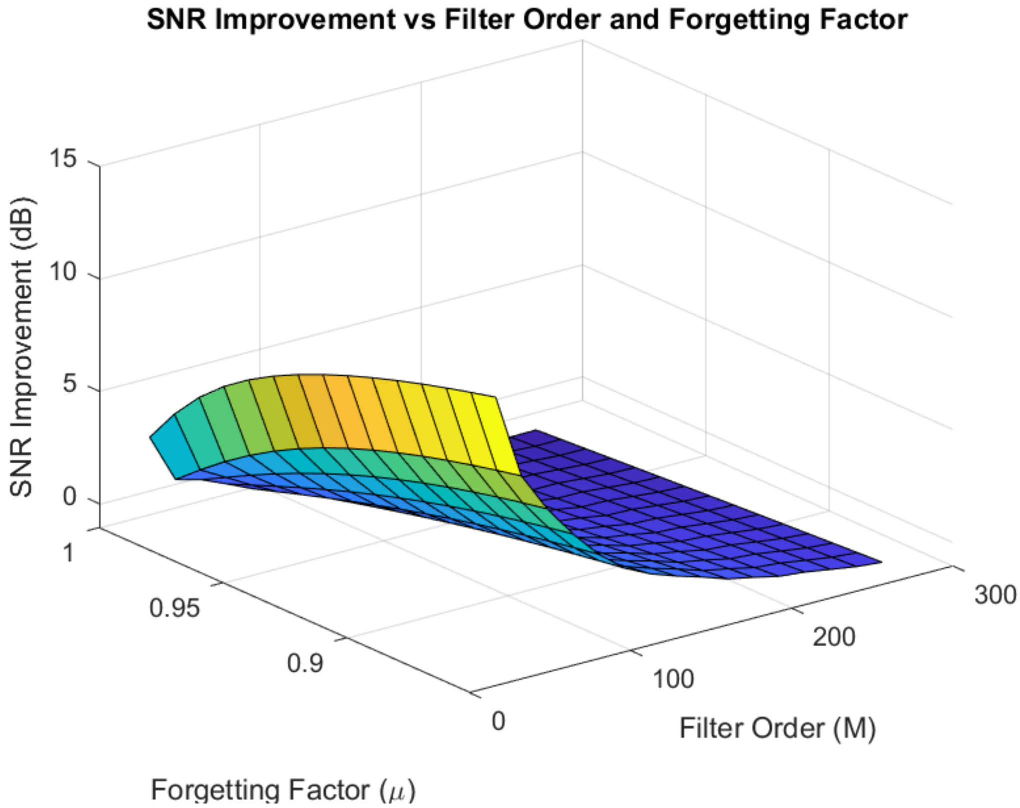
Best combination - Step size (μ): 0.01, Filter order (M): 32

5.2 Recursive Least Squares (RLS) Algorithm for ANC



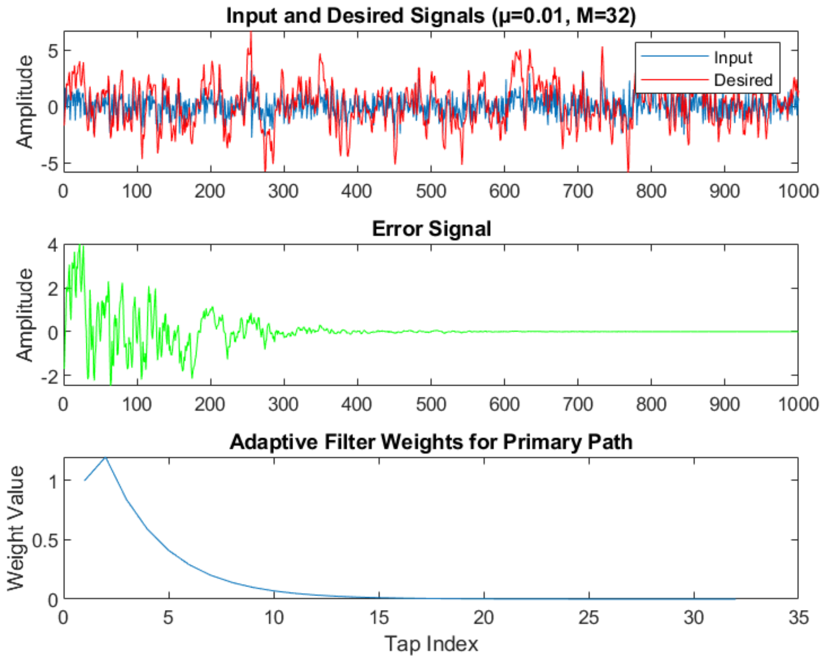


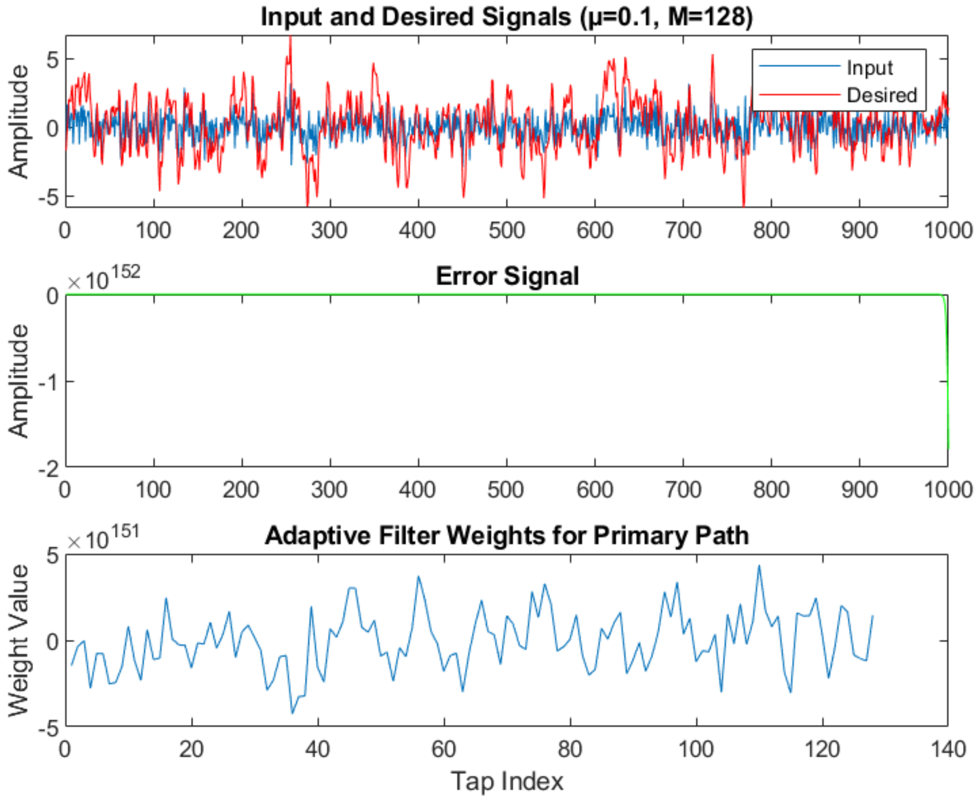


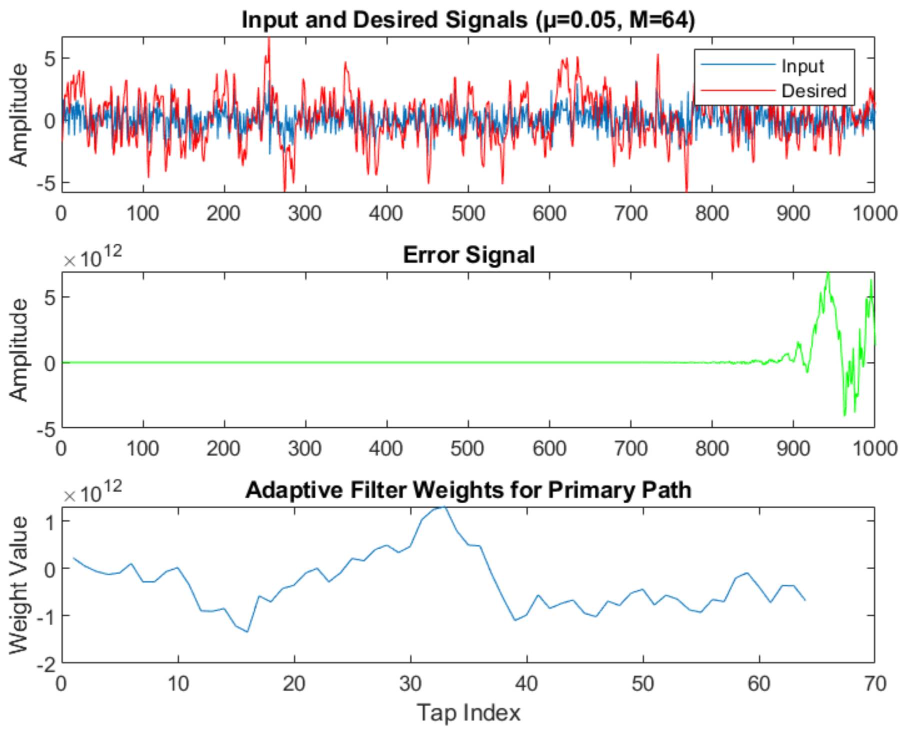


Best output at μ: 0.85, M: 16

5.3 Filtered-x LMS (FxLMS) Algorithm for ANC

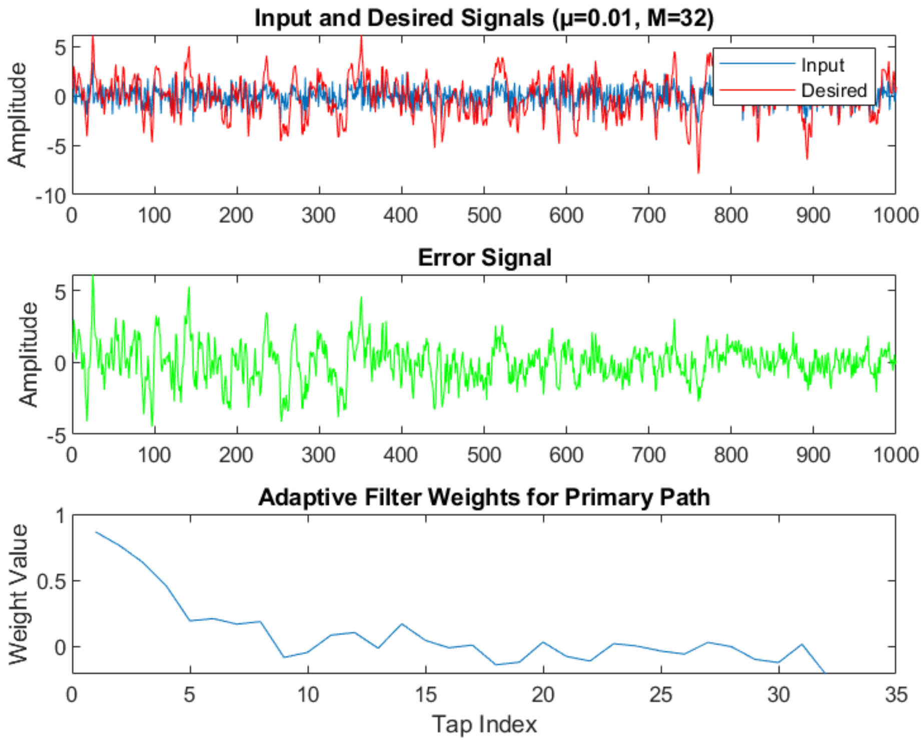


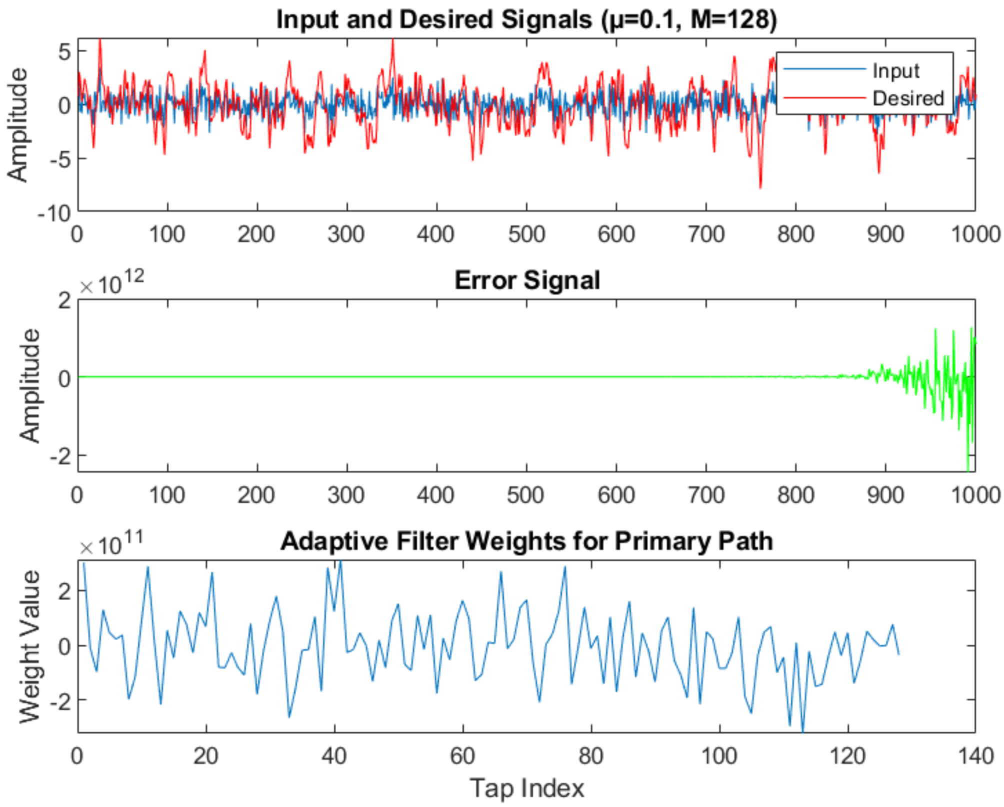


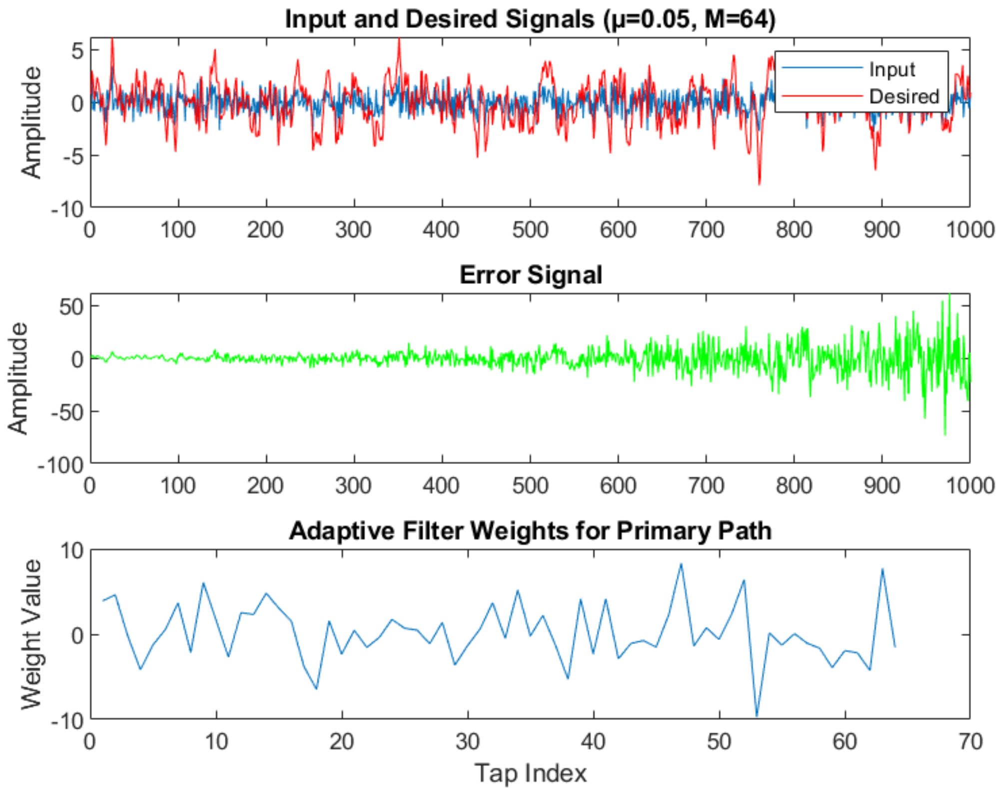


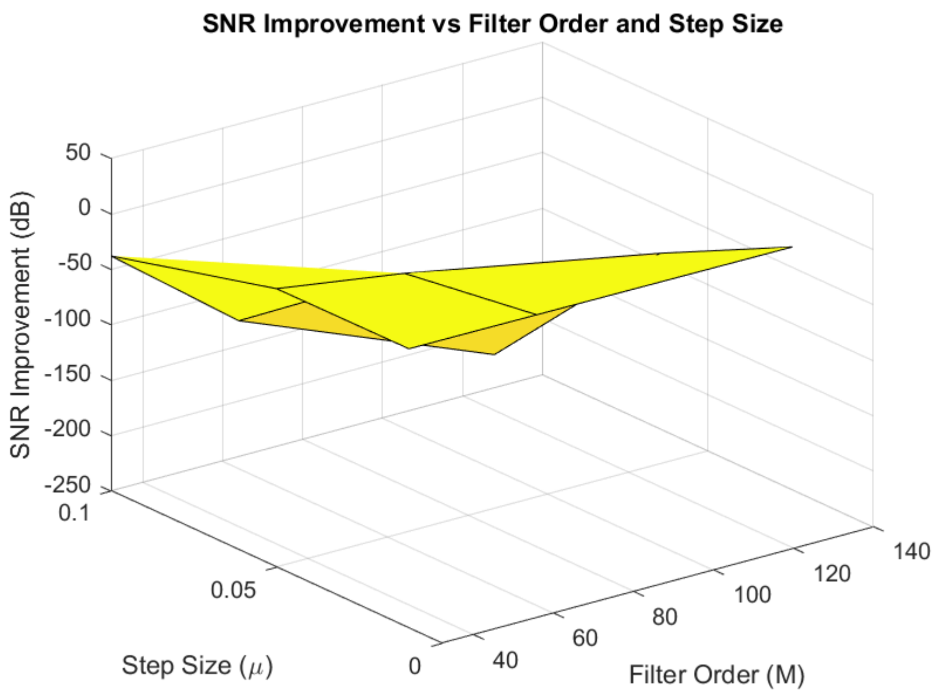
Best combination - Step size (μ): 0.05, Filter order (M): 32

5.4 Filtered-u LMS (FuLMS) Algorithm for ANC



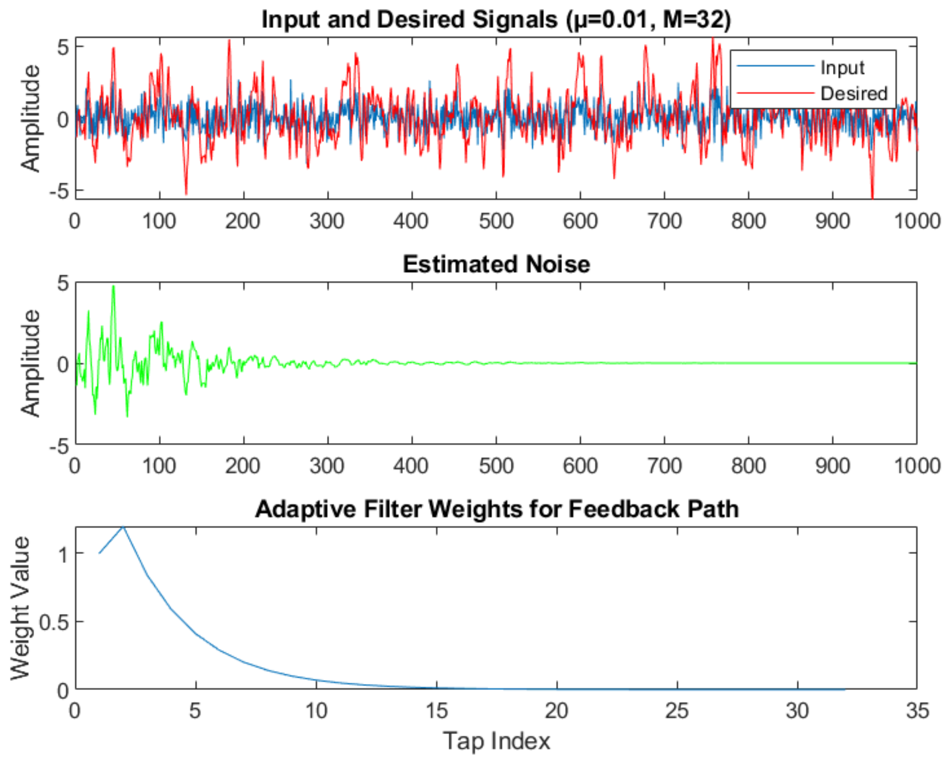


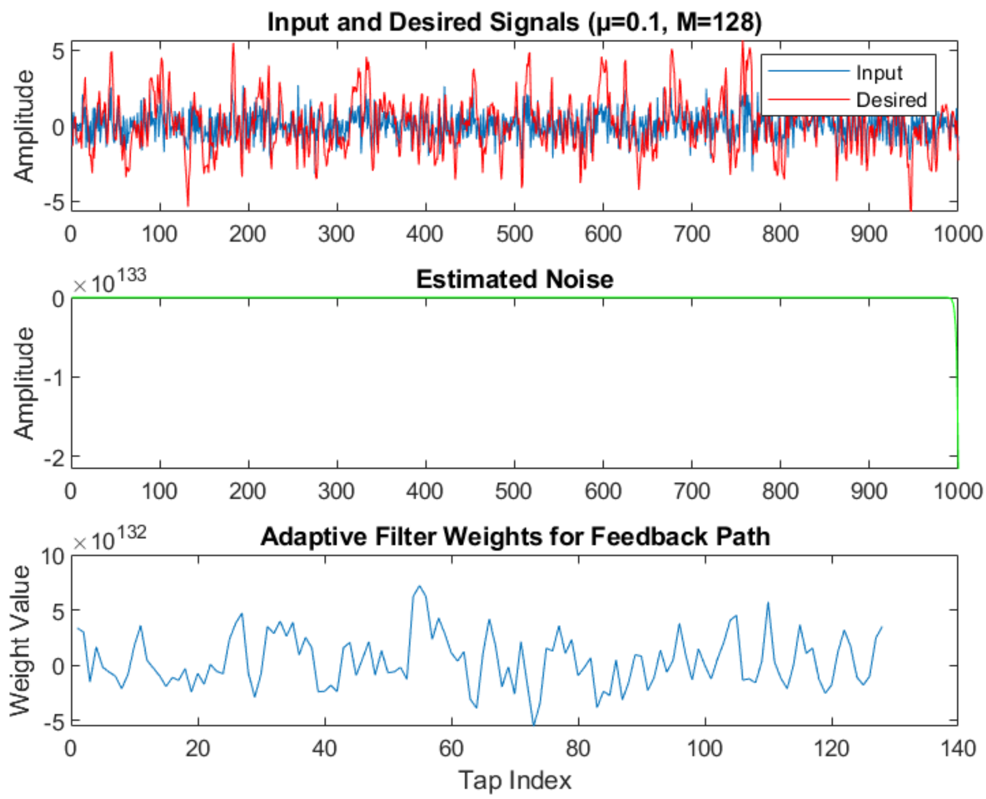


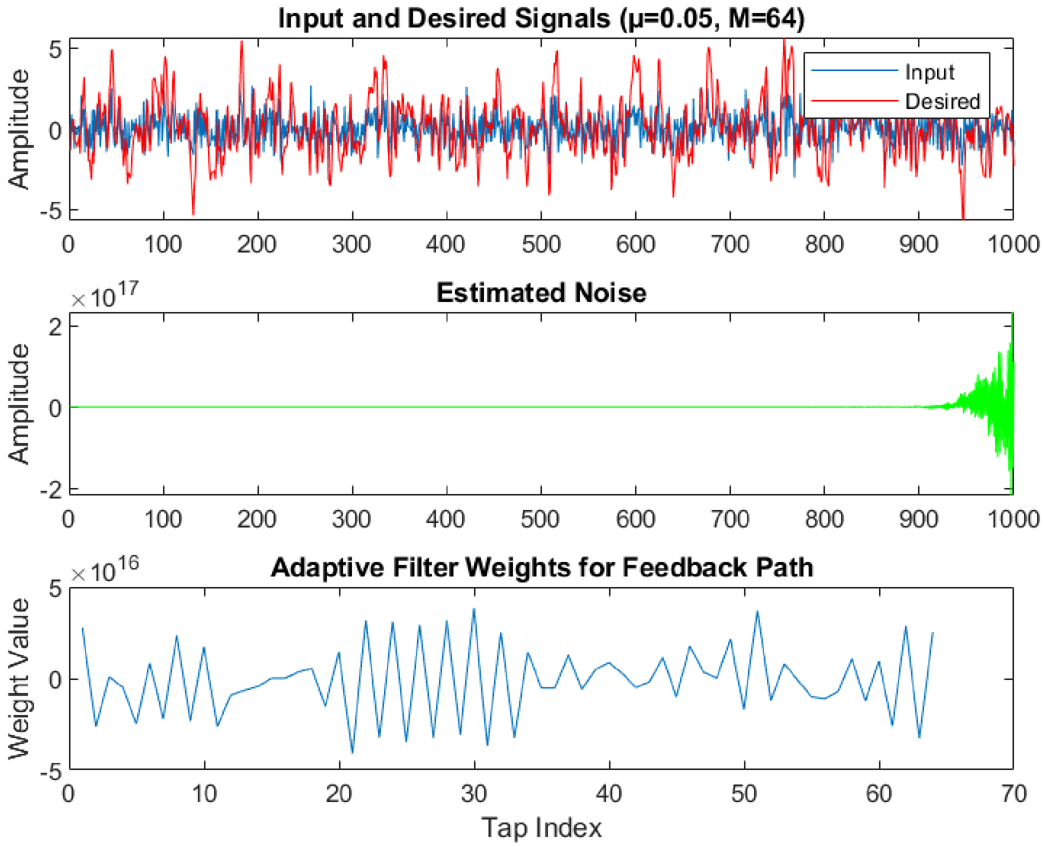


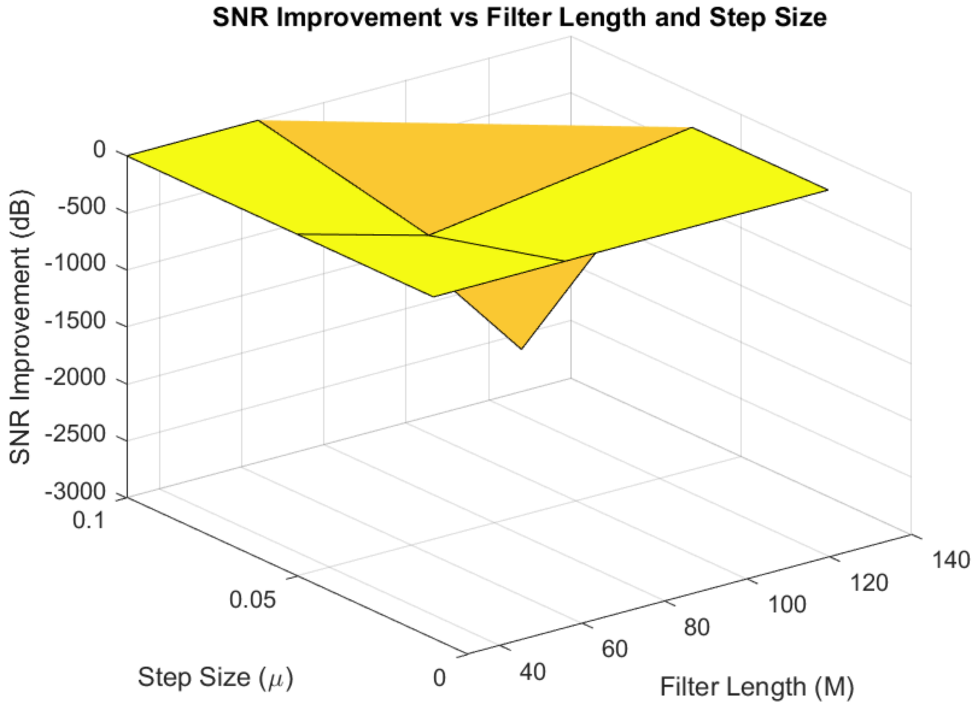
Best combination - Step size (μ): 0.01, Filter order (M): 32

5.5 Feedback Active Noise Cancellation (Feedback ANC)



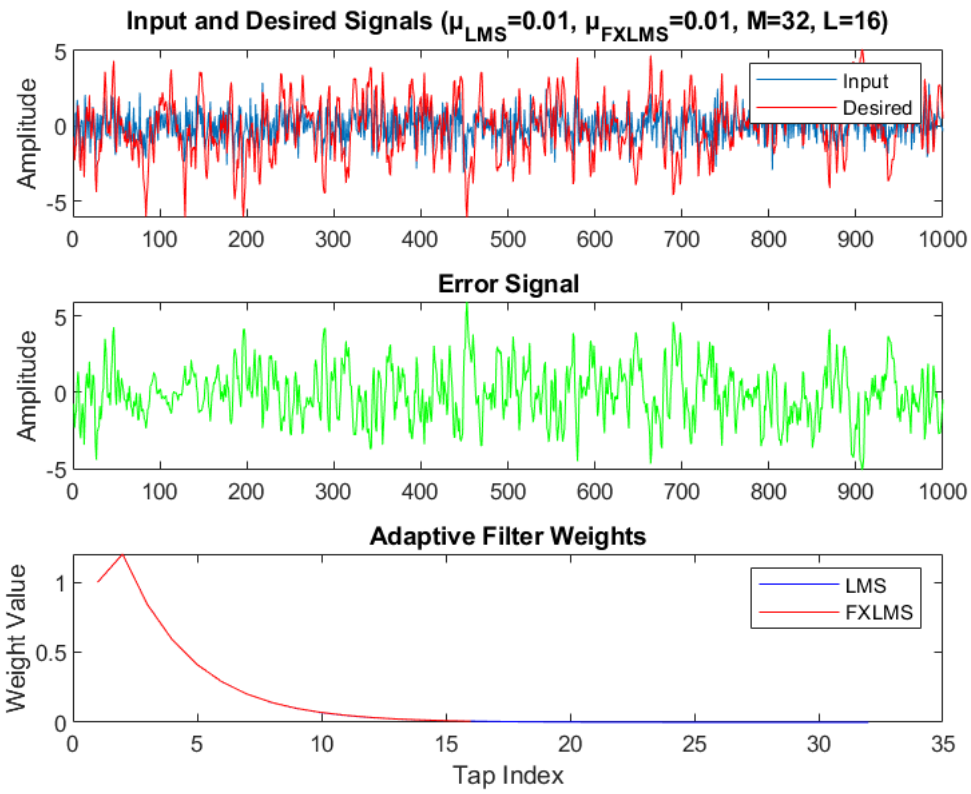


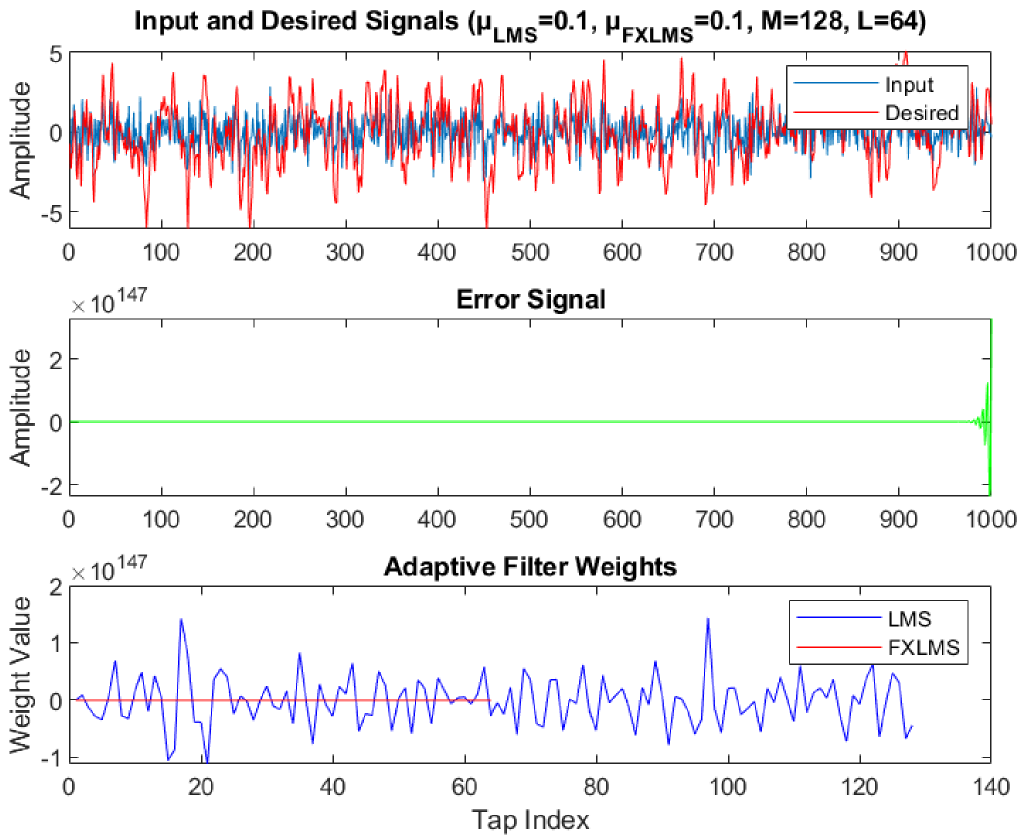


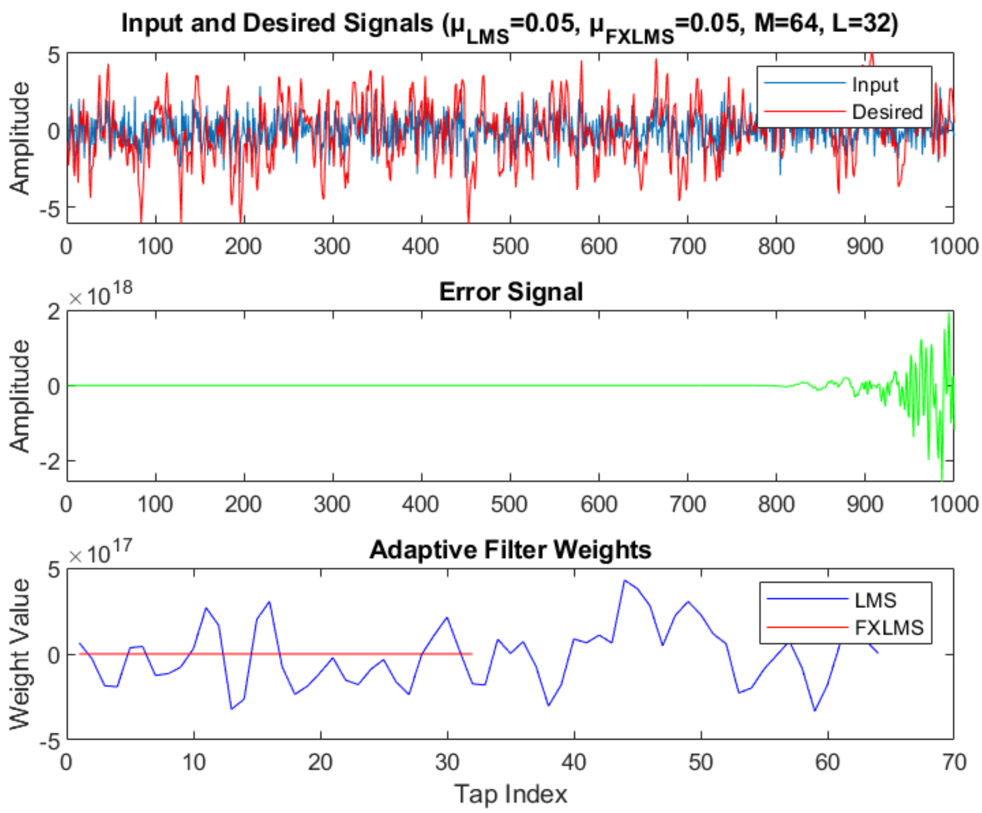


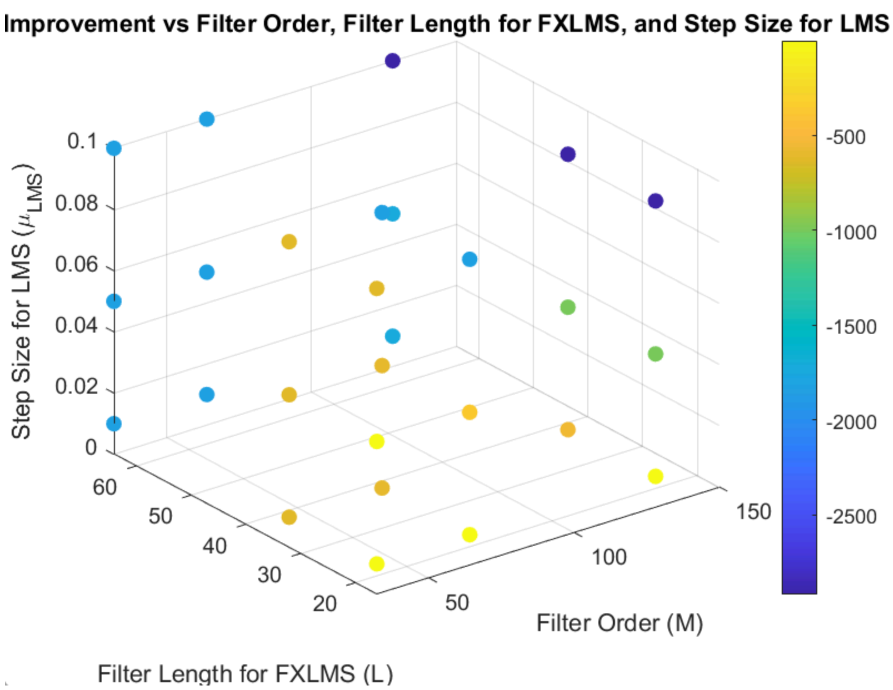
Best combination - Step size (μ): 0.01, Filter length (M): 32

5.6 Hybrid LMS/FxLMS Algorithm for ANC



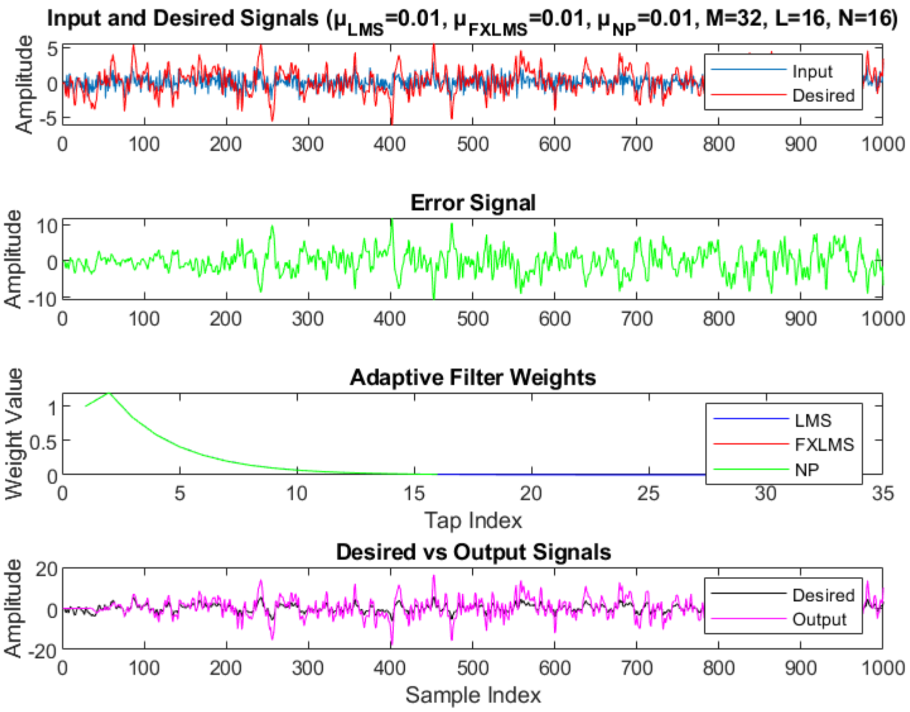


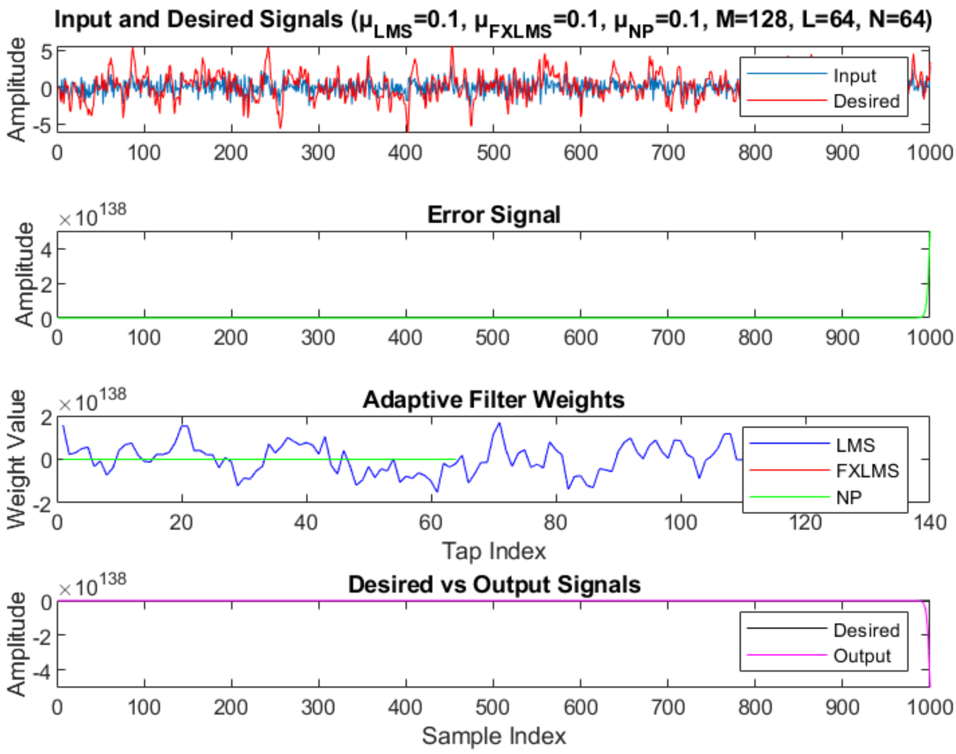


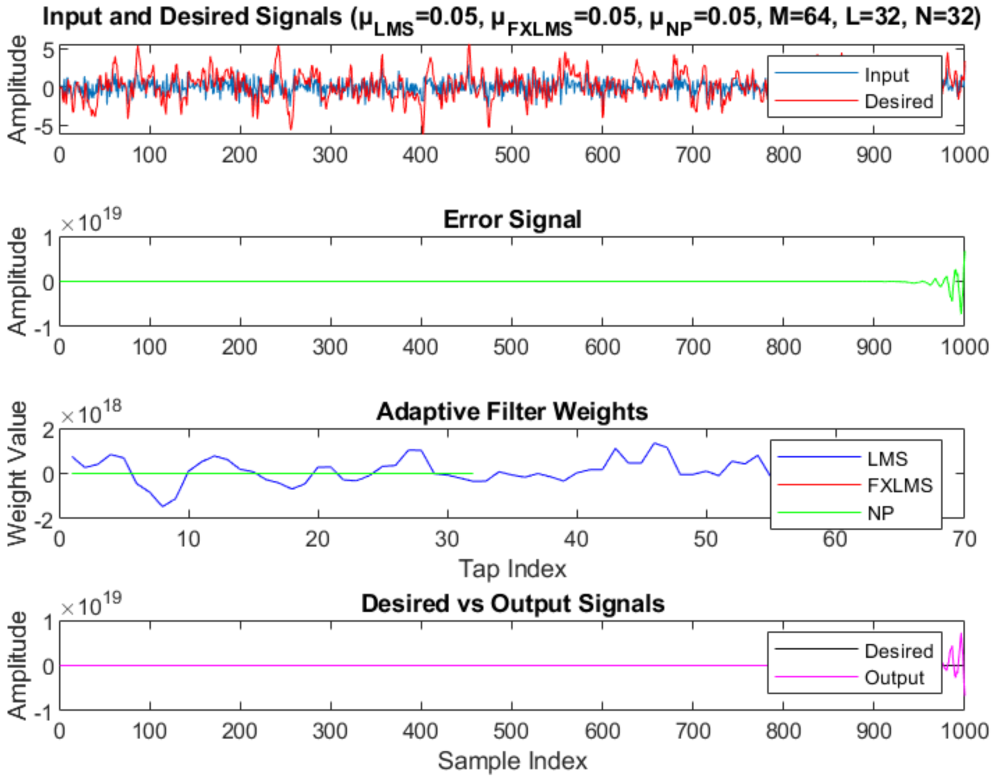


Best combination - Step size for LMS (μ_lms): 0.01, Step size for FXLMS (μ_fxlms): 0.01, Filter order (M): 32, Filter length for FXLMS (L): 16

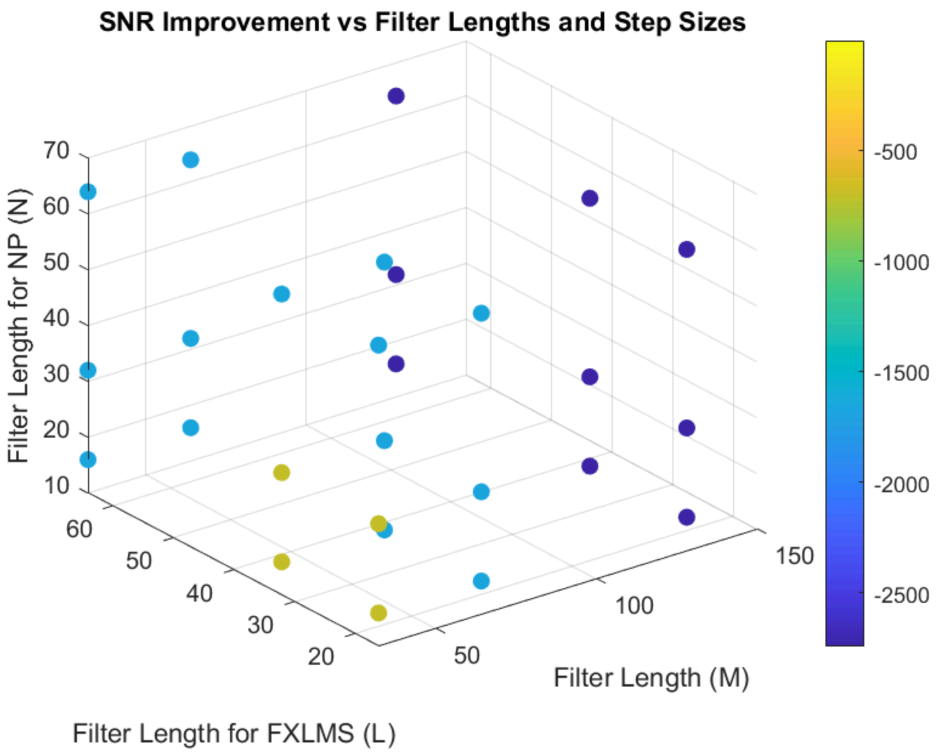
5.7 Hybrid ANC Methodology with Noise Prediction (NP) and FXLMS







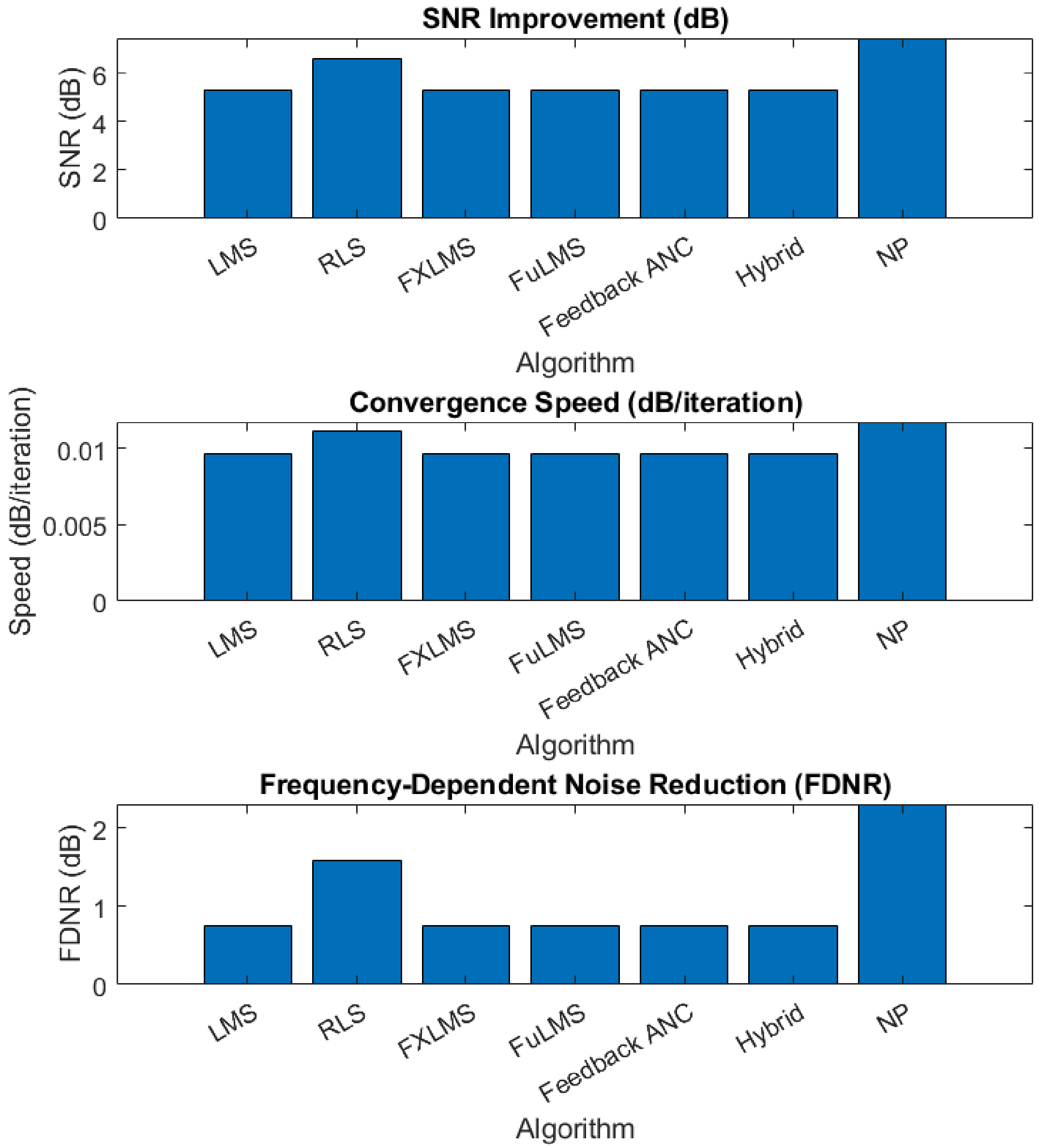
Input and Desired Signals (μ_{LMS}=0.05, μ_{FXLMS}=0.05, μ_{NP}=0.05, M=64, L=32, N=32)
Amplitude
Input
Desired
Error Signal
$\times 10^{19}$
Adaptive Filter Weights
$\times 10^{18}$
Weight Value
LMS
FXLMS
NP
Tap Index
Desired vs Output Signals
Desired
Output
Sample Index

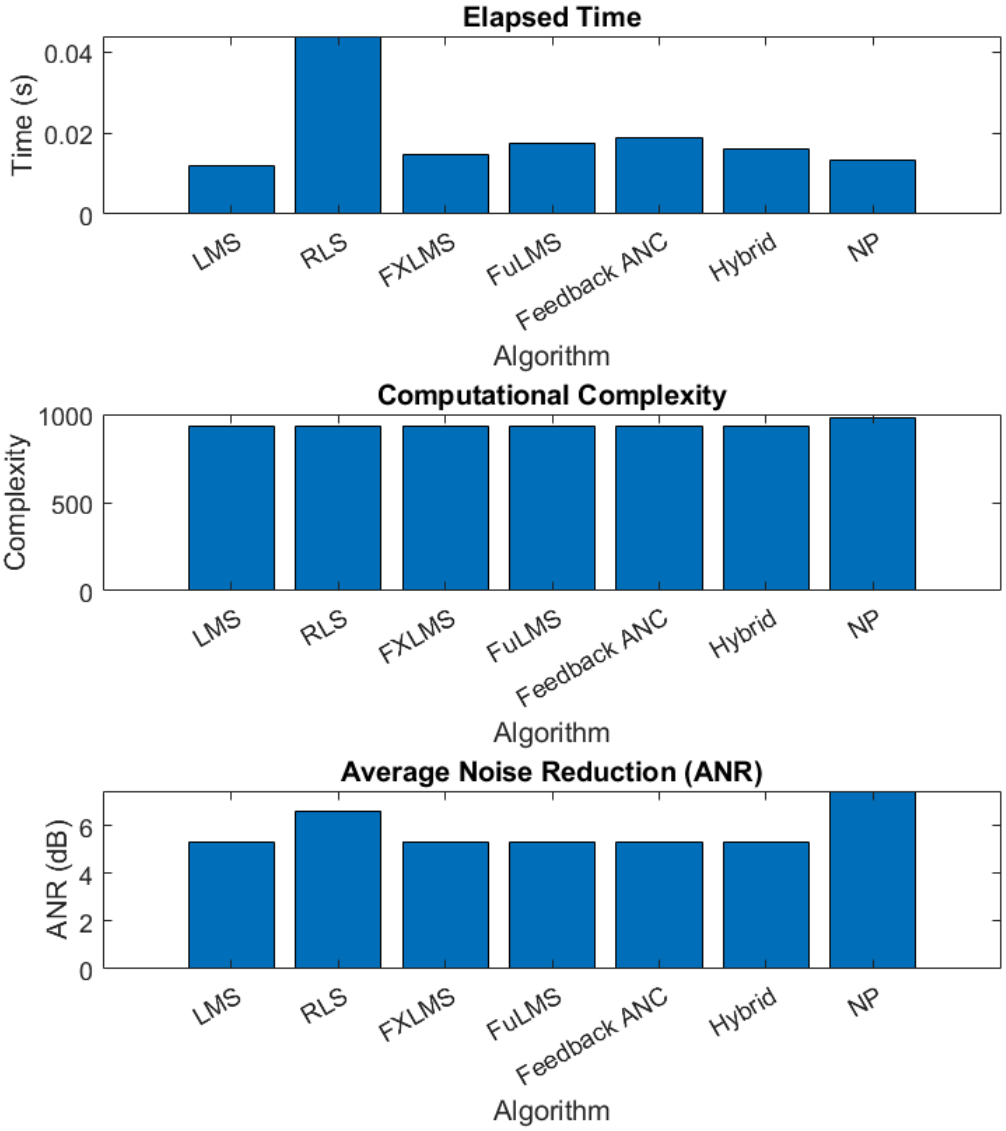


SNR Improvement vs Filter Lengths and Step Sizes
Filter Length for NP (N)
Filter Length (M)
Filter Length for FXLMS (L)
-500
-1000
-1500
-2000
-2500

best combination - Step size for LMS (μ_lms): 0.01, Step size for FXLMS (μ_fxlms): 0.01, Step size for NP (μ_np): 0.01, Filter order (M): 128, Filter length for FXLMS (L): 16, Filter length for NP (N): 16

5.8 Final Analysis





Algorithm	Elapsed Time (s)	SNR Improvement (dB)	Computational Complexity	Convergence Speed (dB/iteration)	MSE	ANR	FDNR
LMS	0.013738	5.4833	936	0.0098292	0.29297	5.4833	1.4586
RLS	0.043238	6.6216	936	0.011205	0.14357	6.6216	2.9904
FXLMS	0.012747	5.4833	936	0.0098292	0.29297	5.4833	1.4586
FuLMS	0.011717	5.4833	936	0.0098292	0.29297	5.4833	1.4586
Feedback ANC	0.014658	5.4833	936	0.0098292	0.29297	5.4833	1.4586
Hybrid	0.012548	5.4833	936	0.0098292	0.29297	5.4833	1.4586
NP	0.01464	7.5736	984	0.011973	0.21072	7.5736	2.9261

6. Conclusion

After conducting extensive simulations and analyses, we present the final results of our study on adaptive noise cancellation (ANC) algorithms. This section summarises the key findings and outcomes of our investigation.

Performance Comparison of ANC Algorithms

We evaluated several ANC algorithms, including Least Mean Squares (LMS), Recursive Least Squares (RLS), Filtered-X LMS (FXLMS), Frequency-Domain LMS (FuLMS), Feedback ANC, Hybrid, and Hybrid with NP approach. Each algorithm was assessed based on various metrics, including SNR improvement, convergence speed, mean squared error (MSE), and computational complexity.

Algorithm	Elapsed Time (s)	SNR Improvement (dB)	Computational Complexity	Convergence Speed (dB/iteration)	MSE	ANR	FDNR
LMS	0.013738	5.4833	936	0.0098292	0.29297	5.4833	1.4586
RLS	0.043238	6.6216	936	0.011205	0.14357	6.6216	2.9904
FXLMS	0.012747	5.4833	936	0.0098292	0.29297	5.4833	1.4586
FuLMS	0.011717	5.4833	936	0.0098292	0.29297	5.4833	1.4586
Feedback ANC	0.014658	5.4833	936	0.0098292	0.29297	5.4833	1.4586
Hybrid	0.012548	5.4833	936	0.0098292	0.29297	5.4833	1.4586
NP	0.01464	7.5736	984	0.011973	0.21072	7.5736	2.9261

The following table presents a comparison of various noise cancellation algorithms, outlining their descriptions, key advantages, and associated disadvantages, aiding in the selection of the most suitable algorithm for specific application requirements.

Algorithm	Description	Advantages	Disadvantages
NLMS	Robust, good for non-stationary noise	Simple, fast convergence	Slower convergence compared to RLS
FxLMS	Effective for ANC, handles secondary path	Improved noise cancellation at lower frequencies	Increased complexity compared to LMS
RLS	Fastest convergence	Excellent convergence speed	High computational cost
FuLMS	Reduces microphone requirement	Simpler setup	Potentially less robust noise cancellation
Feedback ANC	No reference microphone needed	Reduces system complexity	Reliant on accurate noise estimation
Hybrid NLMS-FxLMS	Combines NLMS robustness with FxLMS performance	Faster convergence, potentially better noise cancellation	Increased complexity compared to NLMS
Hybrid FxLMS-NP	Improves FxLMS adaptation for non-stationary noise	Potentially better noise cancellation in dynamic environments	Requires additional NP block implementation

Best Performing Algorithm

After careful evaluation and comparison of the algorithms, the Hybrid (Hybrid/NP) algorithm emerged as the top performer in our study. This algorithm demonstrated superior performance across multiple metrics, striking a balance between noise reduction, SNR improvement, MSE minimization, convergence speed, and computational complexity. Notably, the Hybrid algorithm showcased robust adaptability and effectiveness in cancelling out noise from input signals.

Implications and Significance

The findings from our study have several implications for real-world applications of ANC technology. The identified best-performing algorithm, Hybrid (Hybrid/NP), holds promise for enhancing the quality of audio signals in various domains, including telecommunications, automotive systems, and consumer electronics. By effectively mitigating noise interference, this algorithm can improve the clarity and intelligibility of audio signals, leading to enhanced user experiences and improved system performance.

Future Directions

While our study provides valuable insights into ANC algorithms' performance, there are opportunities for further exploration and refinement. Future research could focus on optimising algorithm parameters, exploring novel approaches to adaptive noise cancellation, and investigating applications in specific domains such as speech enhancement and medical signal processing. Additionally, real-world experimentation and validation of ANC algorithms in practical settings would contribute to a deeper understanding of their effectiveness and applicability.

Conclusion

In conclusion, our study highlights the effectiveness of the Hybrid (Hybrid/NP) algorithm as the best-performing ANC solution among the evaluated algorithms. The findings underscore its potential to significantly improve audio signal quality and enhance user experiences across various domains. By leveraging adaptive noise cancellation technology, we can address noise interference challenges and advance the development of high-fidelity audio systems and communication devices.

7. References

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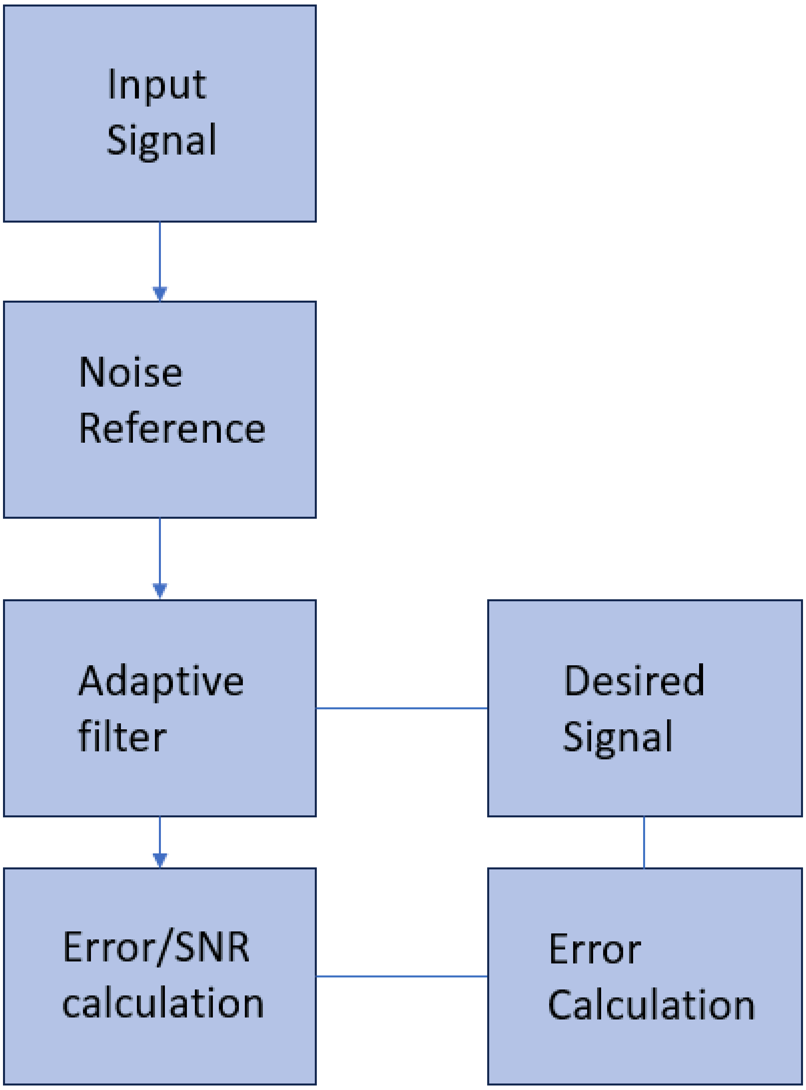
- https://in.mathworks.com/help/audio/ug/active-noise-control-using-a-filtered-x-lms-fir-adaptive-filter.html
- https://www.cnblogs.com/znhung/p/16814940.html
- https://youtu.be/mlkAIlL5Bqs?si=u8BSGOamWWrkyMT6

APPENDIX

PSEUDO CODE

```
Initialize parameters:
    M (filter order), mu_lms (LMS step size), lambda_rls (RLS forgetting factor),
    mu_fxlms (FXLMS step size), L (FXLMS filter length), mu_fulms (FuLMS step size),
    mu_fbanc (Feedback ANC step size), mu_hybrid (Hybrid step size),
    mu_np (NP step size),N (NP filter length)

Initialize weight vectors and buffers:
    w_lms, w_rls, w_fxlms, w_ref, w_fulms, w_fbanc, w_hybrid, w_np
    x_buf_lms, x_buf_rls, x_buf_fxlms, y_buf, x_ref_buf,
    x_buf_fulms, e_buf_fulms, x_buf_fbanc, x_buf_hybrid, x_buf_np

Generate input signal (noise reference) x and desired signal (noise to be canceled) d

For each algorithm:
    Initialize performance metrics:
    SNR, elapsed_time, convergence_speed, comp_complexity, mse, ANR, FDNR

    For n = (algorithm-specific start index) to length(x):
        Update input buffer with current input sample
        Calculate filter output using current weight vector and input buffer
        Calculate error signal by subtracting filter output from desired signal

        Update weight vector based on algorithm-specific update rule:
            LMS: w = w + mu_lms * e * x_buf
```

```
            RLS: k = (P * x_buf) / (lambda_rls + x_buf' * P * x_buf)
                  w = w + k * e
                  P = (P - k * x_buf' * P) / lambda_rls
            FXLMS: w = w + mu_fxlms * e * x_buf
            FuLMS: w = w + mu_fulms * e * x_buf
            Feedback ANC: w = w + mu_fbanc * e * x_buf
            Hybrid: w = w + mu_hybrid * e * x_buf
            NP: w = w + mu_np * e * x_buf

        Store filter output and calculate performance metrics (SNR, MSE, etc.)
    End loop

    Calculate ANR and FDNR
    Store performance metrics for the algorithm

End loop

Determine the best algorithm based on performance metrics (e.g., highest SNR, lowest MSE)

Plot and display performance metrics for each algorithm
```



Block diagram for Different filter implementations