International Journal of Engineering Research and Science & Technology

IJERST

ISSN : 2319-5991



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International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 21, Issue 2, 2025

Speech Enhancement using Time Domain Adaptive Wiener Filtering with LMS and NLMS Algorithm

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ABSTRACT

Speech signals often suffer from degradation due to additive noise, which significantly affects their clarity and intelligibility. To address this issue, an adaptive speech enhancement technique based on the Wiener Filter optimized with the Normalized Least Mean Squares (NLMS) algorithm is proposed. This method operates in the time domain, allowing real-time adaptation to the non-stationary characteristics of speech. Various types of real-world noise—such as traffic, wind, and household appliance noise—are artificially introduced into clean speech recordings for evaluation. The system is tested using different step-size (μ) values of 0.1, 0.2, and 0.3 in the LMS adaptation to analyze convergence behavior and noise suppression performance. Unlike traditional frequency-domain approaches, the time-domain implementation ensures fast convergence and efficient noise suppression while preserving key speech features. The performance of the system is quantitatively assessed using the Mean Squared Error (MSE) metric. Experimental results show that the NLMS-based Adaptive Wiener Filter with LMS adaptation at μ = 0.1, 0.2, and 0.3 provides significant noise reduction and enhanced speech quality. Due to its robustness and low computational complexity, the proposed method is highly suitable for practical applications in telecommunications, hearing aids, and voice-controlled systems.

Keywords—Speech Enhancement, Adaptive Wiener Filter, NLMS, Adaptive Noise Cancellation, Mean Squared Error (MSE), Signal to Noise Ratio (SNR**).**

I. INTRODUCTION

The quality of speech signals often degrades due to the presence of background noise, which significantly impacts speech clarity and the performance of systems reliant on accurate voice input. In high-noise environments, recovering the original speech becomes difficult, leading to errors in communication and system failure. Thus, effective noise suppression is crucial in modern speech processing systems such as telecommunications, voice recognition, and hearing aids.

Speech signals, being one-dimensional time functions, are converted into electrical signals when captured by microphones. Speech enhancement aims to improve intelligibility and perceptual quality by mitigating background noise. Various techniques have been proposed, including spectral subtraction, subspace methods, and adaptive filtering [1]-[2]. Among adaptive filters, algorithms like LMS, NLMS, and RLS have shown effective performance in non-stationary noise conditions.

This work focuses on time-domain adaptive Wiener filtering using the NLMS algorithm for speech enhancement. Unlike traditional frequency-domain methods, this approach adapts in real-time and does not require prior knowledge of noise statistics, offering robustness in dynamic environments [3]–[5]. The NLMS algorithm provides faster convergence and improved stability over standard LMS, making it ideal for real-time applications.

II. LITERATURE REVIEW

Speech enhancement has been an active research area, especially with the increasing demand for improved voice communication systems and robust speech recognition in noisy environments. Over the years, various techniques have been proposed to enhance speech signals corrupted by noise. Traditional methods such as spectral subtraction and Wiener filtering have been widely used, but their performance is often limited in highly non-stationary noise environments.

Recent advancements have seen a shift toward adaptive and learning-based methods for speech enhancement. In [6], the authors proposed a convolutional recurrent neural network (CRNN) for real-time speech enhancement, demonstrating significant improvement in speech quality. However, the computational complexity of deep learning methods may not suit real-time applications with limited resources.

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ISSN 2319-5991 www.ijerst.com
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Adaptive filtering remains a reliable solution in real-time systems. In [7], the performance of NLMS algorithms was explored in wavelet domains for speech enhancement. Their results showed that NLMS provided better convergence and noise reduction than traditional LMS algorithms. Similarly, [8] implemented an adaptive Wiener filtering strategy using time-domain signals and found it to be robust in dynamically changing noise conditions without requiring prior noise statistics.

Another study [9] evaluated different adaptive filtering algorithms such as LMS, NLMS, and RLS, concluding that NLMS offers an optimal trade-off between computational complexity and convergence rate. More recently, [10] implemented real-time adaptive noise filtering in hearing aid systems, showing the practicality of NLMS-based adaptive filtering in constrained environments

Speech enhancement has been a prominent area of research, especially with the increasing use of voice-based systems in real-world noisy environments. Various approaches have been proposed to improve speech quality and intelligibility in the presence of additive noise.
Kinoshita et al. [11] presented a real-time speech enhancement system based on adaptive filtering for mobile communications. Their method emphasized reducing computational complexity while maintaining effective noise suppression. The study demonstrated improvements in latency, making it suitable for embedded systems.

Zhang et al. [12] provided a comprehensive review of deep learning approaches for speech enhancement. While deep models achieved high performance, they require significant computational resources and large training datasets. This limitation makes adaptive filters more suitable for real-time and resource-constrained applications.

Gnanasekaran et al. [13] explored hybrid adaptive filtering techniques and showed that combining LMS and RLS filters improved convergence speed and noise reduction. However, the added complexity may not be feasible for real-time systems

Patel and Sharma [14] compared various adaptive algorithms like LMS, NLMS, and RLS in noise cancellation scenarios. Their evaluation showed that NLMS provides a good balance between convergence rate and computational efficiency, making it preferable in real-time speech processing.

Zheng et al. [15] reviewed a range of adaptive filtering techniques, highlighting the effectiveness of time-domain processing in dynamic noise environments. The study also noted the adaptability and robustness of the Wiener filter when combined with NLMS.

Patel and Sharma [16] compared various adaptive algorithms like LMS, NLMS, and RLS in noise cancellation scenarios. Their evaluation showed that NLMS provides a good balance between convergence rate and computational efficiency, making it preferable in real-time speech processing.
Zheng et al. [17] reviewed a range of adaptive filtering techniques, highlighting the effectiveness of time-domain processing in dynamic noise environments. The study also noted the adaptability and robustness of the Wiener filter when combined with NLMS.

Xia et al. [18] introduced a real-time adaptive Wiener filtering system based on NLMS for voice recognition applications. Their results showed high noise suppression while maintaining low distortion of speech, making it suitable for systems requiring high speech fidelity.
Harish and Choudhary [19] focused on improving speech quality using time-domain adaptive Wiener filters with NLMS optimization. The findings confirmed superior performance over traditional spectral subtraction methods, especially in non-stationary noise environments.
Gupta and Gupta [20] proposed a comprehensive adaptive Wiener filtering framework that improved speech clarity in noisy environments. Their experimental results demonstrated low mean square error (MSE) and high signal-to-noise ratio (SNR), confirming the robustness of the NLMS-based approach.

III. METHODOLOGY

The proposed speech enhancement system employs a time-domain adaptive Wiener filter optimized with the Normalized Least Mean Squares (NLMS) algorithm to suppress additive background noise in speech signals. The methodology consists of several key stages, as outlined below:

3.1 Data Acquisition and Preprocessing

Speech signals are collected either from publicly available databases or recorded using high-fidelity microphones in quiet environments. Real-world noises such as traffic, wind, and household appliance sounds are added artificially to simulate noisy conditions. The sampling rate is standardized (e.g., 16 kHz), and the signals are normalized to a consistent amplitude level**.**

3.2 Adaptive Wiener Filtering

The Wiener Filter is a classical linear filter used for optimal signal estimation and noise reduction in the presence of additive noise. It aims to produce an estimate of the desired signal d(n)d(n)d(n) by minimizing the mean square error (MSE) between the filter output and the desired signal. However, the traditional Wiener filter requires prior statistical knowledge of both the signal and noise, which may not be feasible in real-time or dynamic environments.

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ISSN 2319-5991 www.ijerst.com

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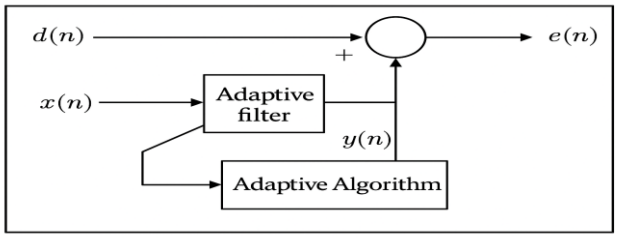


Fig 1. Adaptive Wiener Filter

To address this limitation, the Adaptive Wiener Filter was developed. Unlike the conventional Wiener filter, the adaptive version does not assume stationary signal or noise characteristics. Instead, it updates its filter coefficients iteratively based on the observed data. This makes it particularly suitable for applications like speech enhancement, where the noise and speech characteristics vary over time.

3.3 LMS-Based Adaptive Wiener Filter

The Least Mean Square (LMS) algorithm offers a simple yet effective way to implement the adaptive Wiener filter. It updates the filter weights based on the error between the desired signal and the filter output**:**

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

Where:

w(n) = filter weight vector at time n,

x(n) = input signal vector,

d(n) = desired signal (clean speech),

s^(n)=W^T(n)x(n)=estimated output,

e(n)=d(n)-s^(n)=error signal,

μ=step size parameter.

Although effective, LMS may suffer from slow convergence or instability if μ is not chosen properly.

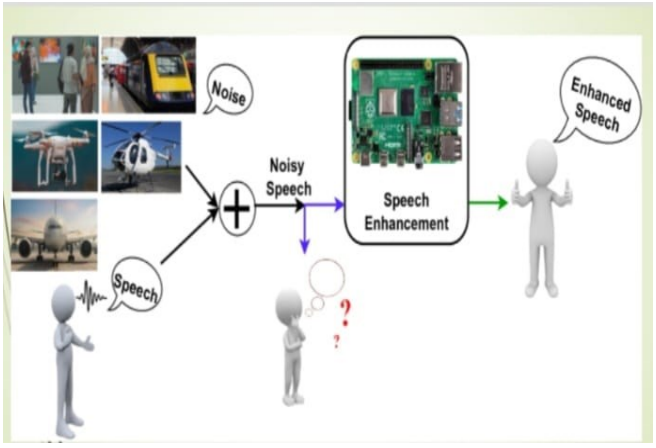


Fig.2 Adaptive Wiener Filter

IV.Adaptive Noise Cancellation Process Using the NLMS Algorithm

Adaptive noise cancellation (ANC) is a signal processing technique aimed at extracting the desired signal from a mixture of that signal and an undesired noise component. In environments where noise is unpredictable and non-stationary (e.g., busy streets, inside vehicles, or industrial machines), traditional filtering techniques fall short. Adaptive filters, on the other hand, dynamically adjust their parameters to track changes in the signal and noise, making them well-suited for such scenarios.

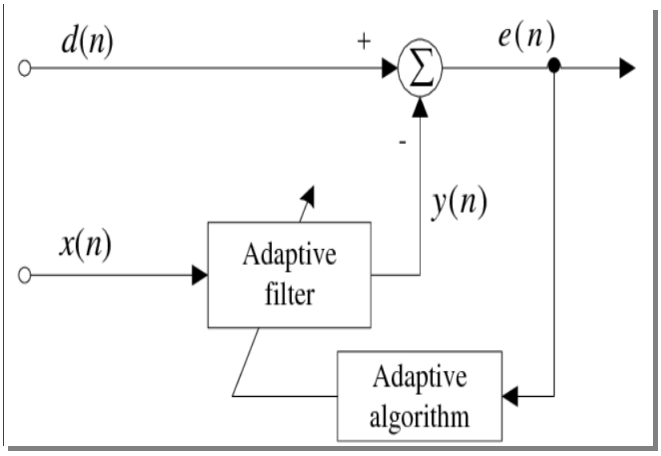


Figure.3 Adaptive Noise Canceller

Among various adaptive filtering algorithms, the Normalized Least Mean Squares (NLMS) algorithm is highly effective for real-time noise cancellation due to its simplicity, low computational complexity, and fast convergence.
The NLMS-based adaptive noise cancellation system works by taking two inputs:

Primary Input: d(n) – contains the desired signal(speech) corrupted with noise.

Reference Input: x(n)x(n)x(n) – a noisy only signal that is correlated with the noise in the primary input.

The adaptive filter tries to model the noise component present in the primary input using the reference input. It then subtracts this estimated noise from the primary signal to produce an enhanced speech output.

Algorithm Description

Let:
x(n) be the reference input vector of length N:

$$\mathbf{x(n) = [x(n), x(n-1), \ldots\ldots, x(n-N+1)]^T - [2]}$$

w(n) be the weight vector of the adaptive filter at time n.

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y(n) be the filter output:

$$y(n) = w^T(n) \cdot x(n) \text{ - [3]}$$

d(n) be the desired signal (noisy speech)

e(n) be the error signal:

$$e(n)=d(n)-y(n) \text{ – [4]}$$

The error e(n)e(n)e(n) represents the difference between the actual noisy speech and the estimated noise. This error is minimized over time by updating the filter weights using the NLMS adaptation rule.

$$w(n+1) = w(n) + \frac{\mu}{\delta + ||x(n)||^2} e(n)x(n) \text{ - [5]}$$

Where:

μ is the step-size parameter that controls convergence speed and stability (commonly **0<μ≤1.**

δ is a small constant to avoid division by zero.

‖x(n)‖2 is the squared norm of the input vector.

This normalization term ensures that the step size adapts to the input signal's energy, enhancing stability and convergence performance, especially in real-time and speech processing tasks.

V .EVALUATION CRITERIA

5.1 Mean Square Error (MSE)

The Mean Square Error (MSE) is a widely used metric for measuring the average of the squares of the errors between the original clean speech signal and the enhanced (denoised) signal. It quantifies the difference between estimated values and actual values.

Mathematical formula:

$$MSR = (1/N) \times \Sigma_{i=1}^{n} (x_i - \hat{x}_i)^2 \text{ - [6]}$$

Where:

x(n): Original clean speech signal.

x^(n): Enhanced speech signal after filtering.

N: Total number of samples

Interpretation:

MSE = 0 implies a perfect match between clean and estimated signal.

5.2 Signal-to-Noise Ratio (SNR)

The Signal-to-Noise Ratio (SNR) is another crucial metric used to assess the quality of speech signals. It measures the ratio of the signal power to the noise power and is typically expressed in decibels (dB).

Mathematical formula:

$$\text{SNR} = 10 \log_{10} \left(\frac{\sum x(n)^2}{\sum (x(n) - \hat{x}(n))^2} \right)$$

- [7]

Where:

x(n): Clean reference speech signal

x^(n): Enhanced (denoised) speech signal

N: Number of samples

Interpretation:

A higher SNR value indicates that the noise level is low compared to the signal, implying better enhancement.

SNR improvement (ΔSNR) is often used to evaluate enhancement:

$$\Delta SNR = SNR_{enhanced} - SNR_{noisy} \text{ - [8]}$$

VI. RESULT AND DISCUSSION

For evaluation purposes, a clean speech signal is taken as the input to the adaptive Wiener filter. This signal is then corrupted individually by three different types of noise: wind noise, traffic noise, and household appliance noise. Each noise is added separately to the speech signal, making it more difficult to comprehend. As a result, noise cancellation becomes essential. To address this, adaptive noise cancellation is applied using an adaptive Wiener filter. The performance of the system is evaluated using the Mean Squared Error (MSE), which quantifies the quality of the output signal. MSE is a non-negative value, and a lower MSE indicates better noise suppression and higher Signal quality.

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Figure 4. The output shows the performance of the Adaptive Wiener Filter for speech enhancement using NLMS Based for Traffic noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

```
Mean Squared Error (MSE): 0.000526
SNR Before Filtering: -4.67 dB
SNR After Filtering : 6.78 dB
```

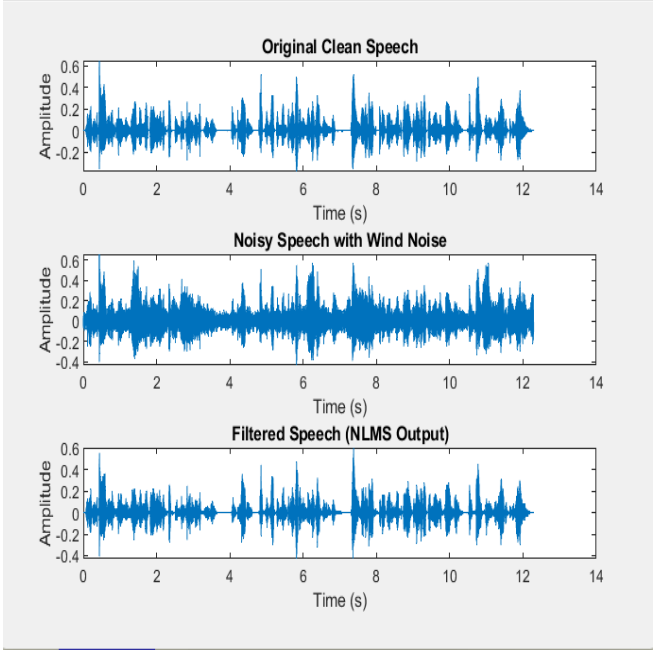


Figure 5. The output shows the performance of the Adaptive Wiener Filter for speech enhancement using NLMS Based for Wind noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

Performance is evaluated using Mean Squared Error (MSE), indicating effective noise cancellation.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

```
Mean Squared Error (MSE): 0.000330
SNR Before Filtering: -1.34 dB
SNR After Filtering : 8.80 dB
```

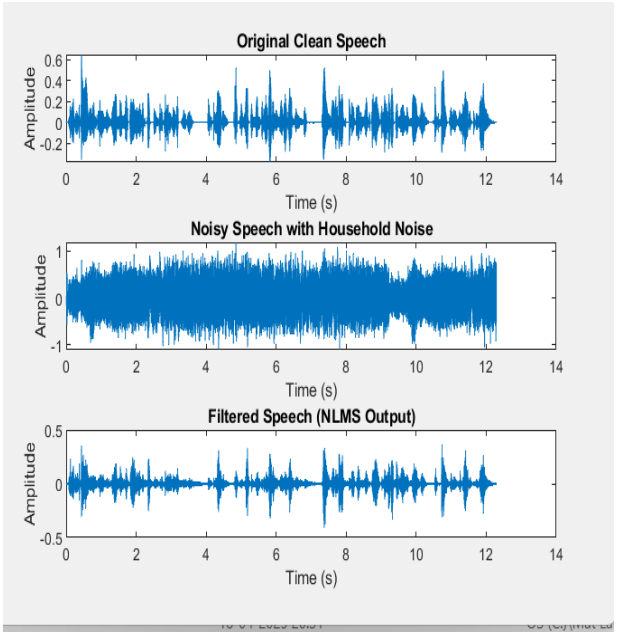


Figure 6 The output shows the performance of the Adaptive Wiener Filter for speech enhancement using NLMS Based for Household noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

Performance is evaluated using Mean Squared Error (MSE), indicating effective noise cancellation.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

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```
Mean Squared Error (MSE): 0.001410
SNR Before Filtering: -14.53 dB
SNR After Filtering : 2.49 dB
>>
```

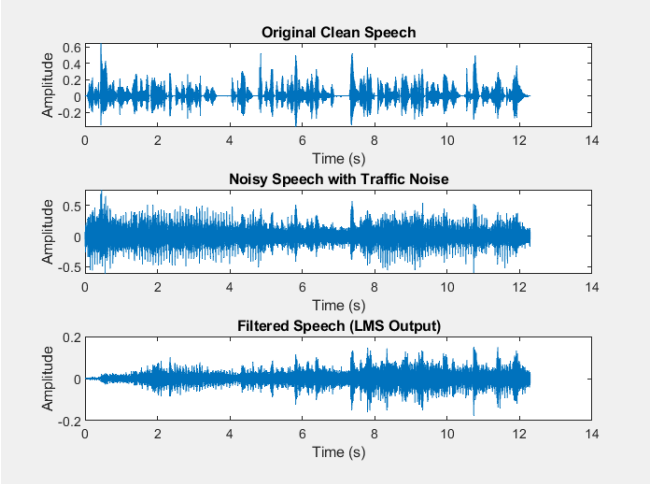


Figure.7 The output shows the performance of the Adaptive Wiener Filter for speech enhancement using LMS Based for Traffic noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

Performance is evaluated using Mean Squared Error (MSE), indicating effective noise cancellation.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

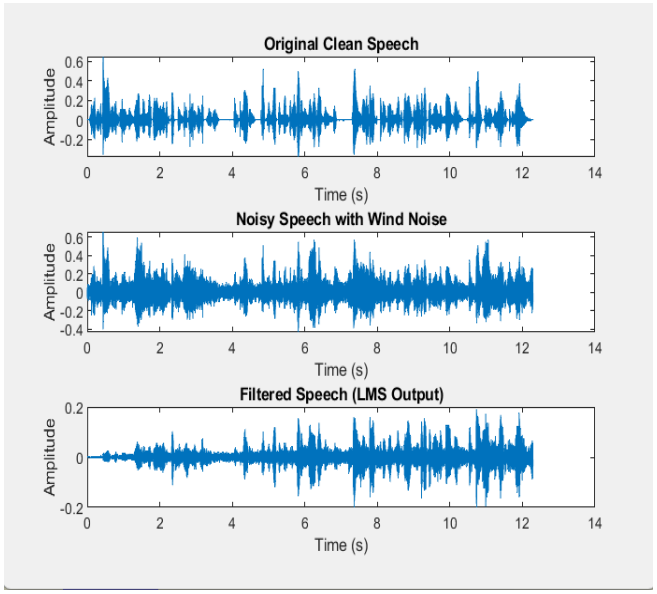


Figure.8 The output shows the performance of the Adaptive Wiener Filter for speech enhancement using LMS Based for Wind noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

Performance is evaluated using Mean Squared Error (MSE), indicating effective noise cancellation.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

```
Mean Squared Error (MSE): 0.001733
SNR Before Filtering: -4.67 dB
SNR After Filtering : 1.60 dB
```

```
Mean Squared Error (MSE): 0.001461
SNR Before Filtering: -1.34 dB
SNR After Filtering : 2.34 dB
```

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ISSN 2319-5991 www.ijerst.com

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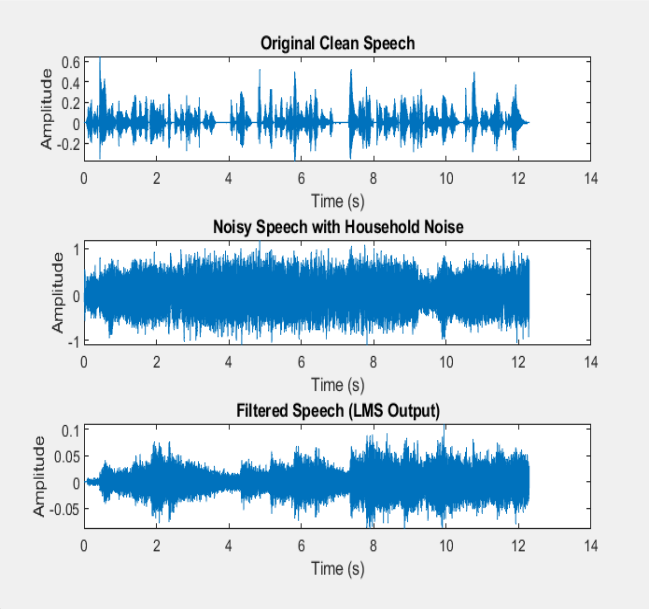


Figure.9 The output shows the performance of the Adaptive Wiener Filter for speech enhancement using LMS Based for Household noise.

Time-domain plots illustrate the difference between original, noisy, and filtered signals.

Performance is evaluated using Mean Squared Error (MSE), indicating effective noise cancellation.

The outputs of MSE and SNR of Traffic Noise Signal are shown in below.

```
Mean Squared Error (MSE): 0.002217
SNR Before Filtering: -14.53 dB
SNR After Filtering : 0.53 dB
```

Noise	μ(step size parameter values)	MSE(mean square error)	SNR(signal to noise ratio) Before filtering	SNR(signal to noise ratio) After filtering
Wind noise	0.1	0.000430	-1.34db	7.66db
Wind noise	0.2	0.000366	-1.34db	8.35db
Wind noise	0.3	0.000330	-1.34db	8.80db
Traffic noise	0.1	0.000703	-4.67db	5.51db
Traffic noise	0.2	0.000592	-4.67db	6.26db
Traffic noise	0.3	0.000526	-4.67db	6.78db
Household noise	0.1	0.001591	-14.53db	1.97db
Household noise	0.2	0.001472	-14.53db	2.31db
Household noise	0.3	0.001410	-14.53db	2.49db

VI. CONCLUSION

In this work, adaptive noise reduction algorithms such as LMS and NLMS were implemented and evaluated under various real-world noise conditions including wind noise, traffic noise, and household appliance noise. The step-size parameter (μ) was varied across three levels—0.1, 0.2, and 0.3—to observe its impact on the performance of the adaptive Wiener Filter. Experimental results demonstrate that the proposed NLMS-based adaptive filtering approach shows consistent improvement in noise reduction and speech quality as the step-size increases from 0.1 to 0.3. Specifically, higher μ values contributed to faster convergence and better noise suppression, while maintaining speech intelligibility. These findings confirm that the proposed algorithm is effective and

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computationally efficient, making it well-suited for practical applications such as telecommunications, hearing aids, and voice-controlled systems operating in noisy environments.

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