International Journal of Electrical Engineering & Emerging Technology, Vol. 07, No. 02, Dec 2024, pp 7-12

Design & Development of Smart Hearing Aid for Hearing Impaired Persons

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[**Received on:** 22-10-2024 **Accepted on**: 13-11-2024 **Published on:** 20-12-2024]

***Abstract*—Hearing loss occurs when the ear, particularly the cochlea, does not function properly. Hearing assistive devices are commonly used to address this issue. Although various hearing aids are available to improve speech signals for individuals with hearing impairments, many still struggle to enhance speech understanding in varying noisy environments. Commonly available hearing devices use static conventional digital filters with fixed cutoff frequencies. As a result, they failed to effectively cancel noise in environments where noise levels vary, limiting their performance in dynamic situations. To overcome these limitations, we propose an adaptive signal processing approach based on the Least Mean Squares (LMS) algorithm. The proposed solution dynamically adjusts the filter weights in response to changes in noise levels, without requiring a reference noise signal. The adaptive hearing aid system is designed to enhance speech quality in noisy listening environments, providing an improved solution for individuals with hearing impairments.**

***Index Terms*— adaptive filter, adaptive signal processing, digital hearing aids, filter order, and noise cancellation.**

I. INTRODUCTION

HEARING problems primarily occur due to improper functioning of the cochlea in the ear. At birth, humans possess thousands of hair cells responsible for sensing electronic sound waves of different frequencies, which are then forwarded to the brain for decoding. Due to factors such as ageing, exposure to loud sounds, drug administration, and infections, the number of these hair cells can decrease. This reduction in hair cells leads to hearing problems, resulting in deafness [1]. Another factor shown in the studies is that background noise can significantly impact speech intelligibility, even for individuals without hearing impairment. It has been established that speech recognition performance decreased by approximately 20% in the presence of moderate background noise [2].

Hearing aids are commonly employed to address hearing impairment by enhancing the speech signal for individuals with hearing loss. Various types of hearing aids are available to improve speech signals for hearing-impaired individuals. Before 1996, analog hearing aids were used, which merely amplified sound without providing noise cancellation. These analog devices offered limited relief, resulting in a negligible proportion of potential wearers.

The introduction of the first digital hearing aid in 1996 revolutionized the hearing aid industry [3]. By using digital signal processing to implement advanced signal processing algorithms. These digital hearing aids provide noise cancellation in noisy environments using advanced digital signal processing techniques. However, modern digital hearing aids still face challenges in environments where noise levels change continuously. Effective noise cancellation is crucial because hearing-impaired individuals struggle to understand speech in the presence of background noise, often missing the original speech signal. Some studies have attempted to address this issue [4-5].

Traditional speech enhancement methods like Spectral Subtraction [6] and statistical model-based methods proposed by Ephraim and Malah [7-8] can be implemented in real time. However, these algorithms do not improve speech quality adequately.

Recent developments in speech enhancement include approaches based on deep neural networks (DNN) [9]. However, these methods are not suitable for real-time applications due to their high computational complexity and the need for extensive training data, making them impractical for implementation on embedded systems.

Multichannel wiener filter has also been used for speech enhancement in hearing aids and noise reduction [10], but this method can also struggle with real-time processing due to its high computational demands, which may exceed the limited resources of hearing aids. Additionally, it may not perform effectively in non-stationary noise environments, leading to inconsistent noise reduction and speech enhancement.

Adaptive filtering, widely used in environments where noise power and bandwidth vary over time, offers a solution to the above-mentioned problems. This paper introduces a digital hearing aid model based on adaptive signal processing that dynamically adjusts without requiring a reference noise signal. The proposed algorithm effectively adapts to changing environmental conditions, thereby enhancing speech perception for individuals with hearing impairments. By using adaptive signal processing techniques, the proposed smart hearing aid aims to improve speech quality in challenging acoustic environment, providing a more effective solution for those with hearing impairments.

II. Normal Hearing Characteristics Of The Human Ear

The human ear can detect sound frequencies ranging from 20 Hz to 20,000 Hz, with peak sensitivity between 1,000 Hz and 5,000 Hz [10]. Sound intensity, measured in decibels (dB), denotes the loudness of a sound wave. Audible sound pressures range from 0 dB, the threshold of hearing, to approximately 120 dB, which can be uncomfortably loud over extended periods (as shown in Fig. 1). Sound waves are variations in air pressure that the ear interprets, enabling us to perceive a broad range of sounds—from the deep rumble of thunder to the high pitch of a bird's song. This understanding is crucial for developing technologies like hearing aids, designed to enhance or modify sound for individuals with hearing impairments.

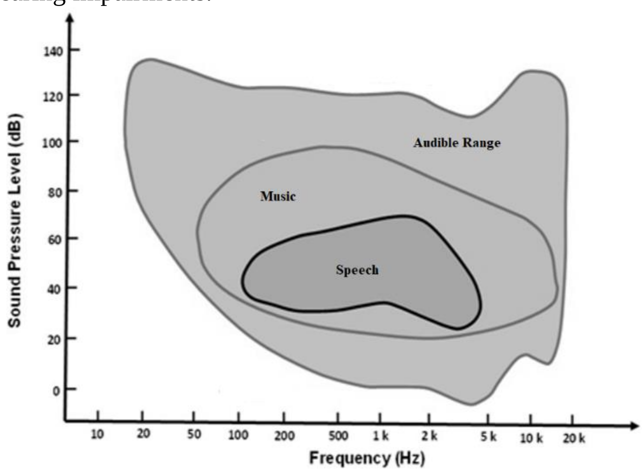

Fig: Normal Human ear's audible range

III. Classification Of Hearing Loss

Various types of hearing loss affect individuals differently, categorized as shown in Table 1. Hearing loss ranges from slight and mild to moderate, severe, and profound. Those with slight or mild hearing loss may struggle to understand normal speech, while individuals with moderate loss find it challenging to comprehend louder speech. Severe cases may require amplified speech to be understood, and those with profound hearing loss may still have difficulty understanding even amplified speech [11]. The quietest sounds or softest intensity levels of sounds that can be perceived by people suffering from different hearing losses are summarized in Table I.

Understanding the classification of hearing loss is crucial in determining appropriate treatments or interventions, such as hearing aids, cochlear implants, or assistive listening devices. Each type of hearing loss can impact communication and daily life differently, underscoring the importance of early detection and personalized management strategies.

TABLE I
CLASSIFICATION OF HEARING LOSS WITH CORRESPONDING DB RANGES AND HEARING CAPABILITIES

Type of Hearing Loss	Description	Hearing Loss Range (dB)
Slight	Difficulty in understanding normal speech	16-25 dB
Mild	Difficulty in understanding louder speech	26-40 dB
Moderate	Difficulty in understanding normal speech, even when raised	41-55 dB
Severe	Can understand amplified speech only	56-70 dB
Profound	Difficulty in understanding amplified speech	71+ dB

IV. Proposed Methodology

In designing a smart hearing aid, the system integrates both hardware and software components, optimized for adaptive signal processing. The hardware includes microphones, digital processors, and speakers, while the software employs adaptive filtering algorithms based on the Least Mean Squares (LMS) method. The hardware setup is shown in the Fig. 2. Together, these elements work seamlessly to enhance the hearing ability by filtering out unwanted noise and improving sound clarity in real-time. It should be noted that the proposed adaptive algorithm does not requires any reference signal for tuning unlike conventional adaptive filtering. This involves continuously monitoring the sound environment and adjusting the filter parameters to enhance speech signals while minimizing background noise.

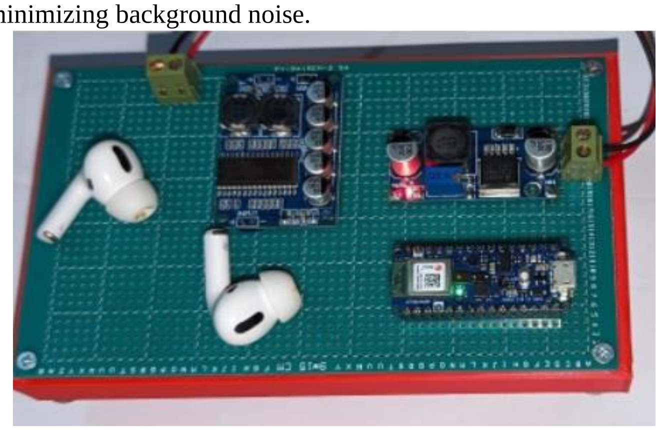

Fig. 2: Hardware implementation of the hearing aid device

A. Adaptive Signal Processing with LMS Algorithm

The LMS algorithm is an adaptive filtering algorithm that aims to minimize the mean square error between the desired signal and the actual output. In this context, the desired signal is the delayed version of the noisy speech signal, and the output x(n) is the noisy speech signal received by the microphones. The LMS algorithm iteratively updates the filter coefficients to reduce the error, thus enhancing the speech signal.

The LMS algorithm can be expressed mathematically as follows:

$$y(n) = \sum_{i=0}^{N-1} Wi(n).x(n) \quad (1)$$

$$e(n) = x(n-1) - x(n) \quad (2)$$

$$Wi(n+1) = Wi(n) + \mu.e(n).x(n) \quad (3)$$

Where y(n) is the output signal, x(n) is the input signal, Wi are the filter coefficients, e(n) is the error signal, μ is the Convergence Factor known as convergence factor, and N is the filter length [12].

This approach allows the hearing aid to continuously adapt to changing environmental noise conditions, providing improved speech intelligibility for the user. By leveraging the LMS algorithm, the hearing aid can effectively filter out background noise without requiring a separate reference noise signal, making it suitable for real-time applications [13] [14].

B. Working Principle

In Fig. 3, it shows that first of all speech signal is captured by a mic then it enters into a sum block, and a delayed version of the speech signal is input into the adaptive system. From the sum block the subtraction will occur between speech signal x(n) and its delayed version x(n-1). After subtraction between these two signals, an error signal e(n) will be taken as an output from the sum block and this error signal e(n) will be fed back into the adaptive system. Based on this error signal e(n), the adaptive system will update its coefficient. This process will continue until the error signal e(n) approaches to zero. At the last stage, the desire clean signal will be taken as output.

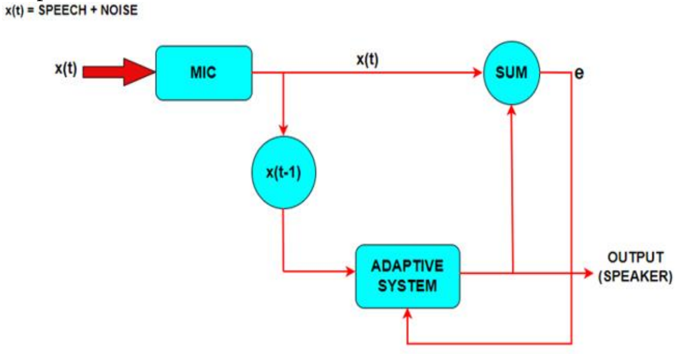

Fig. 3: Block Diagram of proposed Adaptive System

V. RESULT

In this section, we present the results of our proposed adaptive hearing aid device by analyzing the performance under varying conditions. We conducted experiments using different step sizes and filter orders to observe their impact on the Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE). Each experiment was designed to validate the algorithm's adaptability and efficiency across multiple scenarios, including varying noise levels and speech conditions. By systematically adjusting the Convergence Factorand filter order, we aimed to identify the optimal configurations that enhance the device's performance, thereby improving the overall hearing experience for impaired users. The time domain and frequency domain analysis plots are plotted for each case.

A. Case I

In first case, the proposed algorithm was tested with a filter order of 32 and a convergence factor(μ) of 0.01. The filter order determines the complexity and accuracy of the adaptive filter, while the convergence factor controls the rate of adaptation. The performance of the algorithm was assessed using the Mean Squared Error (MSE), which was found to be 0.00051154, indicating a low level of error between the desired and filtered signals, demonstrating the algorithm's effectiveness in enhancing speech clarity by significantly reducing noise. The noisy and the filtered signal is shown in the Fig. 4.

To further evaluate the filter's response based on the filter order and convergence factor, the algorithm was initially tested with a filter order of 100 and a convergence factor of 0.01. Following this, the same filter order was tested with a slower convergence factor of 0.001. Subsequently, the filter order was increased to 200, and the tests were repeated for both convergence factors (0.01 and 0.001). The results, as shown in Table II, demonstrate that with the increase in both the filter order and the convergence factor, the performance of the proposed algorithm improved, particularly in terms of Mean Squared Error (MSE). This suggests that a higher filter order and an optimized convergence factor contribute to enhanced accuracy in noise cancellation and better overall performance of the algorithm.

The time domain and frequency domain analyses of the remaining cases, as previously discussed, are detailed below. These analyses provide insight into how the proposed algorithm performs across different signal conditions, evaluating the filter's ability to reduce noise and enhance the desired speech signal. In the time domain, the effectiveness of noise cancellation is observed by comparing the original and filtered signals. Meanwhile, the frequency domain analysis offers a clear representation of the signal's spectral content, showcasing how various frequency components are impacted by the filtering process. Each case demonstrates specific performance metrics, such as Mean Squared Error (MSE) with respect to different filter order and convergence factor.

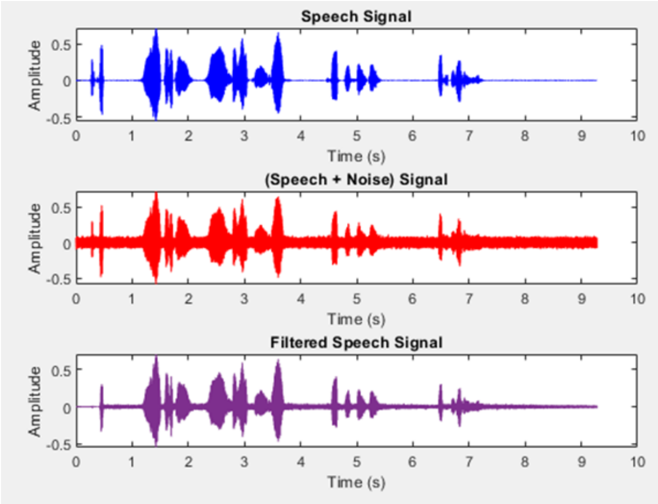

Fig. 4. Time domain analysis Case I

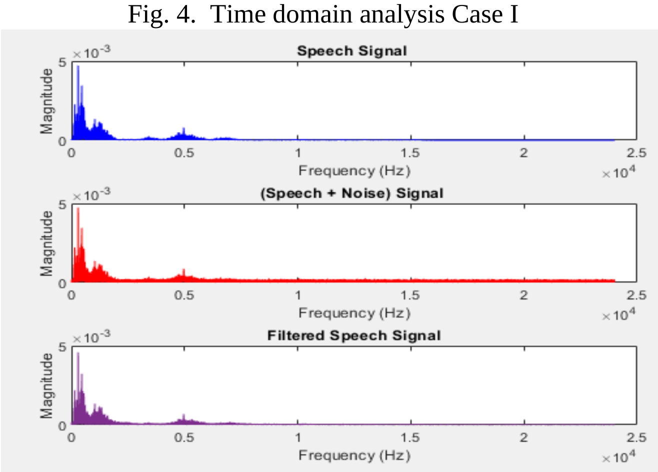

Fig. 5. Frequency domain analysis Case I

B. Case II

Filter order: 100
Convergence Factor(μ): 0.01
Mean Squared Error (MSE): 0.00049263

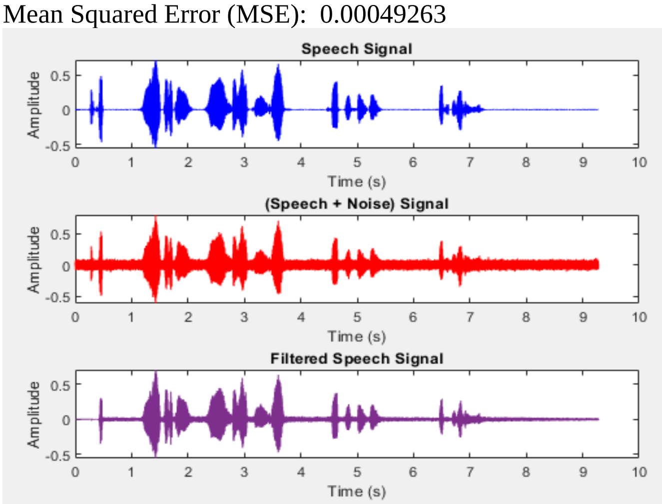

Fig. 6. Time domain analysis Case II

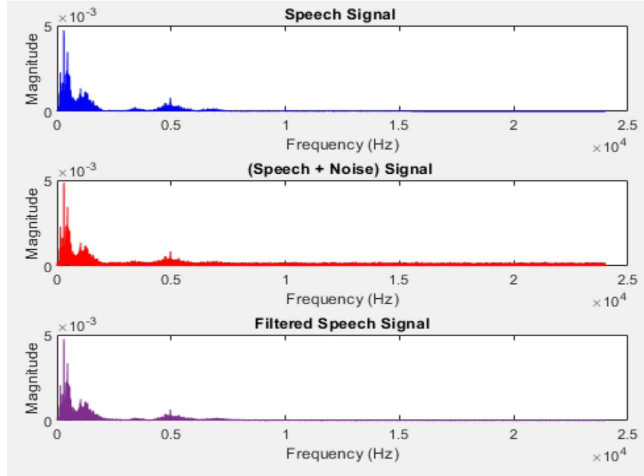

Fig. 7. Frequency domain analysis Case II

C. Case III

Filter order: 100
Convergence Factor(μ): 0.001
Mean Squared Error (MSE): 0.00012981

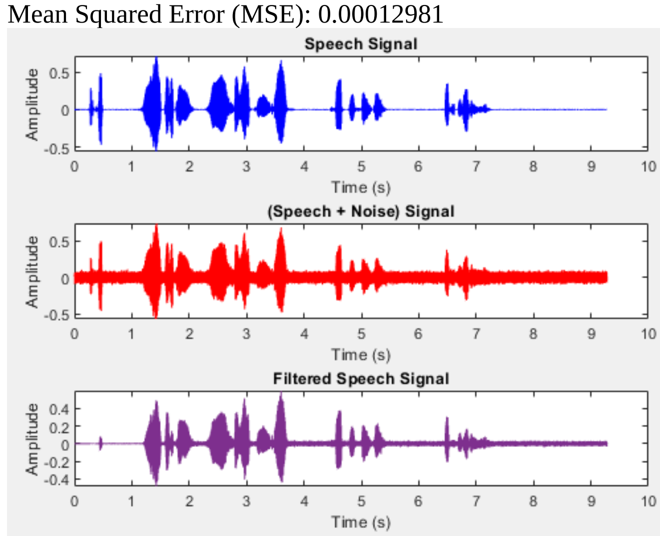

Fig. 8. Time domain analysis Case III

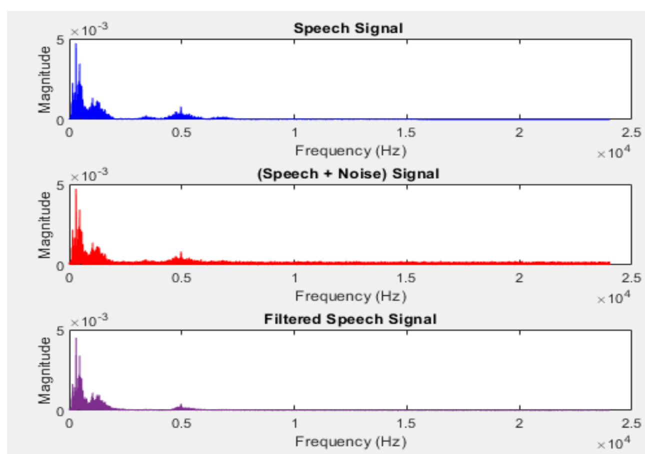

Fig. 9. Frequency domain analysis Case III

D. Case IV

Filter order: 200
Convergence Factor(μ): 0.001
Mean Squared Error (MSE): 0.00032059

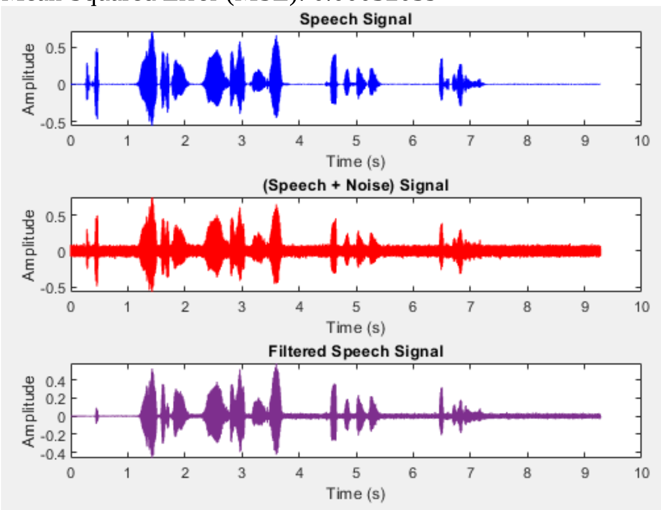

Fig. 10. Time domain analysis Case IV

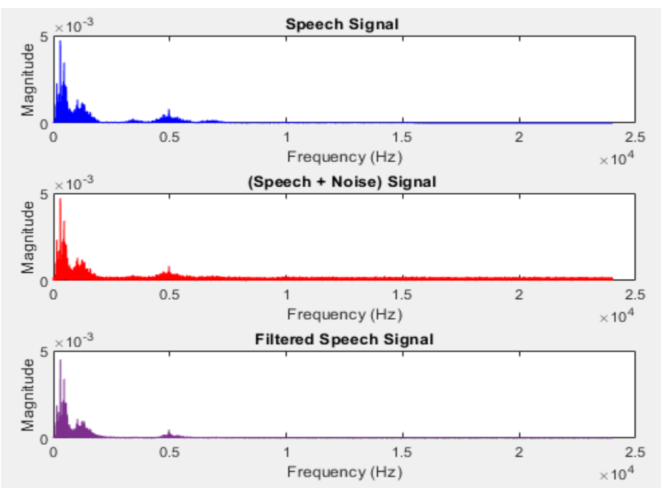

Fig. 11. Frequency domain analysis Case IV

E. Case V

Filter order: 200
Convergence Factor(μ): 0.0001
Mean Squared Error (MSE): 0.00011555

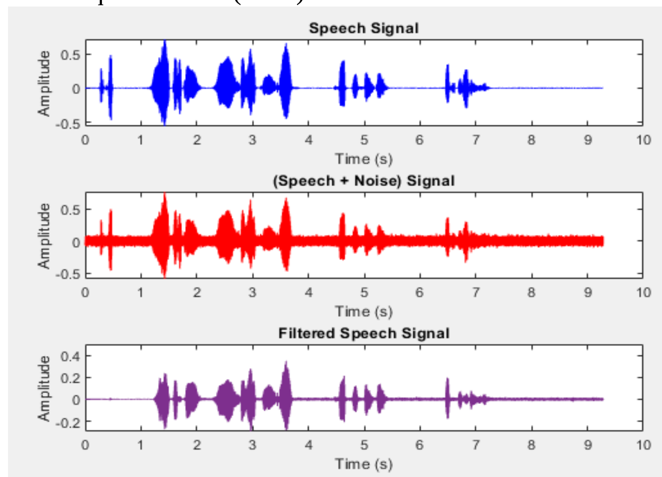

Fig. 12. Time domain analysis Case V

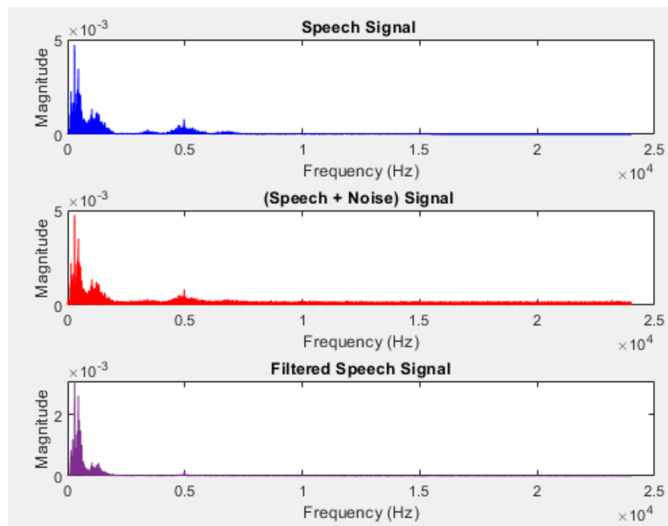

Fig. 13. Frequency domain analysis Case V

All the above cases are summarized in the TABLE II below. Against every convergence factor and filter order, the mean square error (MSE), and SNR value of the filtered signal are listed.

TABLE II
PROPOSED ADAPTIVE HEARING AID PARAMETERS

Case	**Filter Order**	**Convergence Factor(μ)**	**MSE**
I	32	0.01	0.00051154
II	100	0.01	0.00049263
III	100	0.001	0.00012981
IV	200	0.01	0.00032059
V	200	0.001	0.00011555

VI. Conclusion

This paper presents the design and development of a smart hearing aid utilizing adaptive signal processing based on LMS algorithm to enhance speech for individuals with hearing impairments. The main advantage of the proposed solution is its ability to cancel the noise within the speech signal without requiring a separate noise reference signal. This feature simplifies its application in real-world environments where noise characteristics are constantly changing. By analyzing different filter orders and step sizes, the study shows that the comparable performance of the proposed algorithm in terms of MSE and PSD. The results highlight the importance of selecting appropriate filter parameters; a higher filter order improved the filter's performance in mitigating the noise. while an optimal convergence factor balanced stability and convergence speed, leading to enhanced speech clarity and reduced noise.

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