18ECP109L-PROJECT
LEAKY LMS BASED LOW COMPLEXITY ADAPTIVE NOISE CANCELLATION

A PROJECT REPORT

Submitted by

SWAPNIL MAITI [RA2111004010283]
DEEKSHITHA ADUSUMALLI [RA2111004010290]
KUNAL KESHAN [RA2011004010051]
SAHIL SHARMA [RA2011004010252]

Under the guidance of

DR. S. HANNAH PAULINE

(Assistant Professor, Department of Electronics and Communication Engineering)

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

ELECTRONICS & COMMUNICATION ENGINEERING

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

COLLEGE OF ENGINEERING AND TECHNOLOGY

SRM. NAGAR, Kattankulathur-603203,

Chengalpattu District

MAY 2025

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

(Under Section 3 of UGC Act, 1956)

BONAFIDE
CERTIFICATE

Certified that this project report titled “PCG Signal Denoising Using Switched Adaptive Filtering Technique with low-Complexity” is the bonafide work of “**SWAPNIL MAITI [RA2111004010283], DEEKSHITHA ADUSUMALLI [RA2111004010290], KUNAL KESHAN [RA20104010051], SAHIL SHARMA [RA20104010252]** who carried out the project my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

DR HANNAH PAULINE
ASSISTANT PROFESSOR
Dept. of Electronics and
Communication Engineering

SIGNATURE

Dr. M. SANGEETHA
HEAD OF THE DEPARTMENT
Dept. of Electronics &
Communication Engineering

Signature of the Internal Examiner

Signature of the Internal Examiner

ABSTRACT

Phonocardiogram (PCG) signals are acoustic recordings that capture the complex sounds generated by the heart, commonly acquired using a stethoscope or specialized microphones. These recordings are essential in revealing details of the heart's mechanical actions, such as the movement of valves and the dynamics of blood flow, offering valuable insights into cardiovascular health. By analyzing distinct heart sounds in PCG signals—using digital signal processing to measure timing, frequency, and intensity—healthcare providers can accurately identify heart-related conditions, including valve abnormalities and murmurs. However, PCG signals are often disrupted by noise from surrounding environmental sounds, patient movements, respiratory sounds, and electronic interference, which can compromise the precision of analysis. This interference can obscure critical cardiac sounds, potentially leading to diagnostic errors or missed conditions. To ensure the reliability of PCG-based assessments, effective noise reduction techniques—such as advanced filtering and adaptive noise cancellation—are necessary, helping to preserve signal clarity and enable accurate cardiac monitoring.

ACKNOWLEDGEMENT

We would like to express our deepest gratitude to the entire management of SRM Institute of Science and Technology for providing me with the necessary facilities for the completion of this project.

I wish to express my deep sense of gratitude and sincere thanks to our Professor and Head of the Department Dr. Sangeetha M, for her encouragement, timely help, and advice offered to me.

I am very grateful to my guide Dr. Hannah Pauline Assistant Professor, Department of Electronics and Communication Engineering, who has guided me with inspiring dedication, untiring efforts, and tremendous enthusiasm in making this project successful and presentable.

I would like to express my sincere thanks to the project coordinator Dr. T. Deepa for her time and suggestions for the implementation of this project.

I also extend my gratitude and heartful thanks to all the teaching and non-teaching staff of the Electronics and Communications Engineering Department and to my parents and friends, who extended their kind cooperation using valuable suggestions and timely help during this project work.

SWAPNIL MAITI
DEEKSHITHA
KUNAL KESHAN
SAHIL SHARMA

TABLE OF CONTENTS

ABBREVIATIONS

LMS-Least Mean Square

LLMS – Leaky Leasy Mean Square

PCG – Phonocardiogram

CHAPTER 1

INTRODUCTION

The analysis of phonocardiogram (PCG) signals and speech signals is crucial for a variety of medical and communication-related applications. These signals, however, are often exposed to interference from a wide range of external noise sources, which can significantly reduce their quality. This degradation can compromise the accuracy of diagnoses in medical contexts or hinder effective communication in everyday interactions. In the case of PCG signals, which capture the sounds associated with the beating heart, any background noise can obscure vital cardiac events such as the opening and closing of heart valves, potentially leading to missed diagnoses or incorrect assessments of heart conditions. Similarly, speech signals, essential for clear communication, are often contaminated by ambient noise, particularly in environments with high levels of background sound or during the transmission of speech through communication systems. Such noise reduces clarity and intelligibility, impacting communication effectiveness and user experience.

To address these challenges, noise reduction techniques are essential. One such technique that has proven effective is Least Mean Squares (LMS) algorithm. This advanced algorithm offers a robust solution for reducing noise in both PCG and speech signals. The LMS algorithm, in its basic form, works by iteratively adjusting filter coefficients to minimize the difference between a desired signal and the noisy input signal. While effective, the standard LMS algorithm can sometimes be unstable, particularly in dynamic, non-stationary environments where the characteristics of noise change rapidly over time. This is where the "leakage" factor, incorporated into the multistage version of the algorithm, provides a significant advantage.

The multistage Leaky LMS algorithm works by introducing a "leakage" factor into the adaptation process, which helps to prevent instability during prolonged filtering. The leakage factor acts as a damping mechanism, allowing the filter to respond more smoothly to changing noise conditions without losing important signal features. By progressively refining the signal in multiple stages, the algorithm can adapt more effectively to complex and time-varying noise sources, leading to a clearer, more accurate restoration of the original signal.

This ability to adapt in real-time makes the multistage Leaky LMS algorithm an ideal tool for noise cancellation in both medical diagnostics and communication systems. In medical settings, the preservation of subtle details in heart sounds is critical for diagnosing cardiovascular conditions. For instance, detecting early signs of heart valve dysfunction or arrhythmias requires the clear identification of specific heart sounds that could be obscured by environmental noise. The multistage Leaky LMS algorithm ensures that these crucial sounds are preserved, improving the accuracy of diagnoses and the overall effectiveness of heart health monitoring.

In Parkinson’s disease, speech difficulties such as slurred articulation, reduced volume, and monotone voice often hinder effective communication. These challenges can impact daily interactions and overall quality of life. The multistage Leaky LMS algorithm offers a potential solution by filtering out unwanted noise and enhancing speech clarity. By improving intelligibility, this technique helps individuals with Parkinson’s disease communicate more clearly, fostering better social interactions and confidence in verbal expression.

Ultimately, the integration of the multistage Leaky LMS algorithm represents a significant advancement in noise reduction techniques, benefiting both medical diagnostics and communication systems. By effectively reducing noise while preserving the essential features of heart sounds and speech, this approach holds great promise for improving the reliability and clarity of PCG and speech signals. In complex and noisy environments, it ensures that critical details remain intact, supporting more accurate diagnoses in healthcare settings and enabling more effective communication across various platforms. As the technology continues to evolve, its impact on both healthcare and communication systems will likely expand, making it a cornerstone of future advancements in these fields.

CHAPTER 2

LITERATURE SURVEY

YEAR AND PUBLICATION	**TOPIC**	**INFERENCE**
Published in 2023 in IEEE.	Hardware Co-Simulation of Adaptive Noise Cancellation System using LMS and Leaky LMS Algorithms	This paper discusses the co-simulation approach for implementing adaptive noise cancellation using LMS and Leaky LMS algorithms, showing improved noise cancellation efficiency when implemented in hardware setups like FPGA.
International Journal of Electronics and Communications, 2022,	Implementation of Optimized Adaptive LMS Noise Cancellation System to Enhance Signal to Noise Ratio	The paper focuses on optimizing the LMS algorithm to improve the signal-to-noise ratio (SNR) in communication systems, demonstrating significant performance enhancements in various noise environments.

Journal of Signal and Information Processing,2023.	A Comparative Study on Characteristics and Properties of Adaptive Algorithms applied to Noise Cancellation Techniques	This study compares various adaptive algorithms like LMS, RLS, and NLMS, analyzing their strengths and weaknesses in noise cancellation applications, providing insights into selecting the most suitable algorithm for specific use cases.
Published in 2022 in the Journal of Signal and Information Processing.	A Comparative Study on Characteristics and Properties of Adaptive Algorithms applied to Noise Cancellation Techniques	This study compares various adaptive algorithms like LMS, RLS, and NLMS, analyzing their strengths and weaknesses in noise cancellation applications, providing insights into selecting the most suitable
IEEE Transactions on Signal Processing	Performance Analysis of Adaptive Filters for Noise Cancellation in Various Environments	The paper discusses the performance of different adaptive filter algorithms in various noise environments, providing a comparative study on their effectiveness.
Multidimensional Systems and Signal Processing 33, 1387-1408 (2022).	A low-cost automatic switched adaptive filtering technique for denoising impaired speech signals.	The proposed adaptive filter model, which combines LMS and NLMS algorithms, effectively reduces noise in speech signals, particularly those affected by Parkinson's disease. This model outperforms existing filters by significantly improving SNR, MSE, and PSNR, offering a

		cost-effective solution for adaptive noise cancellation with high accuracy.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Statement of the Problem

Speech signal degradation caused by noise interference poses a significant challenge in both medical diagnostics and communication systems. Background noise from various sources, such as crowded environments, urban settings, and transmission channels, can obscure essential speech components, leading to reduced intelligibility for both human listeners and automated recognition systems. In medical applications, particularly in speech-based diagnostics for disorders such as dysphonia and Parkinson's disease, noise contamination can result in misinterpretations, complicating early detection and treatment. Furthermore, the presence of noise reduces the reliability of speech recognition technologies, impacting their effectiveness in healthcare and communication domains. Given these challenges, there is a critical need for advanced noise reduction techniques to enhance speech clarity, improve diagnostic accuracy, and optimize the performance of automated speech processing systems.

3.2 Challenges in Speech Signal Processing:

The challenges in speech signal processing primarily stem from background noise and channel distortions that degrade the clarity of speech signals. Noise can arise from various sources, such as environmental sounds or technical interferences during transmission, causing the desired speech signal to become mixed with unwanted elements. This mixture results in poor speech recognition and synthesis, affecting both human and machine interpretations. For instance, automatic speech recognition (ASR) systems struggle to accurately decode words when background noise is present, leading to errors in transcription or failure to recognize key words. Furthermore, distortions introduced by the communication channels can alter the frequency or amplitude of the speech signal, further complicating the processing task. These challenges demand sophisticated noise suppression techniques to maintain speech clarity, but many current methods are computationally intensive and ill-suited for real-time applications. Hence, finding a suitable solution that balances effectiveness with computational efficiency remains a critical goal in the field of speech processing.

3.3 Existing Solutions:

Existing techniques for reducing noise in speech signals include methods like wavelet transforms, deep learning models, and empirical mode decomposition (EMD). These approaches have demonstrated varying degrees of success in filtering out unwanted noise from speech signals. Wavelet transforms, for instance, are effective at capturing both time and frequency information, making them useful for non-stationary noise reduction. Deep learning methods, particularly neural networks, can adapt to complex and dynamic noise environments, often yielding impressive results in noise reduction and speech enhancement. EMD is another method that decomposes signals into intrinsic mode functions, facilitating noise removal without losing key speech features. However, these techniques often come at a high computational cost, requiring substantial processing power and time to implement. As a result, they are not well-suited for real-time applications, where low-latency performance is essential. Despite their effectiveness, these solutions pose challenges in terms of implementation in systems that need to operate efficiently and swiftly, especially in mobile or embedded devices that require real-time speech signal processing.

3.4 Proposed Solution:

The multistage Leaky Least Mean Squares (LLMS) adaptive filtering algorithm offers a promising alternative for noise reduction in speech and phonocardiogram (PCG) signals. This algorithm is known for its simplicity and low computational complexity, making it ideal for real-time applications. The key advantage of the Leaky LMS approach is its ability to achieve rapid convergence while suppressing noise effectively, even in dynamic and non-stationary environments. The "leakage" factor incorporated in this algorithm prevents instability during prolonged filtering, allowing it to maintain the stability of the filter and ensuring that important features of the signal are preserved. In the case of speech signals, this results in clearer, more intelligible speech even in noisy environments. For PCG signals, the Leaky LMS algorithm enhances the detection of critical cardiac events, such as valve movement and heartbeat sounds, which might otherwise be masked by background noise. By leveraging multiple stages of filtering, the multistage version of the Leaky LMS algorithm further enhances its adaptability, progressively refining the signal to provide optimal noise reduction. This approach offers a balanced solution that reduces noise without sacrificing computational efficiency, making it a viable option for real-time processing in both medical diagnostics and communication technologies.

3.5 Scope Of Study:

The scope of this study focuses on the application of the multistage Leaky Least Mean Squares (LLMS) adaptive filtering algorithm for denoising speech and phonocardiogram (PCG) signals. The goal is to explore how this algorithm can effectively reduce noise in both medical and communication systems, enhancing the clarity and accuracy of these critical signals. Specifically, the study will investigate the algorithm's performance in real-time environments, where noise reduction is crucial for accurate diagnostics and effective communication. The research will examine how well the multistage Leaky LMS algorithm adapts to varying noise conditions, both in terms of environmental interference in speech signals and physiological noises in PCG signals. Additionally, the study aims to assess the computational efficiency of the algorithm, ensuring that it can meet the performance requirements of real-time systems without demanding excessive processing resources. By focusing on both speech and PCG signal enhancement, this study hopes to contribute to the development of more reliable and effective noise reduction technologies in fields like healthcare, telecommunication, and speech recognition systems.

3.6 Realistic Constraints

Sensitivity to Input Signal Characteristics: The effectiveness of the adaptive filter is heavily influenced by the characteristics of the input signal. For instance, PCG signals vary widely in terms of the noise environment, signal strength, and the nature of the heart sounds themselves. If the noise is highly variable or has significant low-frequency components, the adaptive filter may struggle to effectively separate the noise from the desired signal. Likewise, the presence of strong environmental interference or electronic artifacts can complicate the filter’s ability to converge to the optimal solution. The filter's ability to adapt to these changing conditions in real-time can be limited, especially in the case of non-stationary noise, where the noise characteristics evolve over time.

The step size is a critical parameter that must be carefully tuned to achieve optimal performance. However, it can be difficult to select a step size that is optimal for all scenarios. In real-world applications, PCG signals can vary greatly depending on the individual patient, the equipment used, and the environmental conditions. Therefore, a step size that works well in one scenario may not be effective in another. Manual tuning of the step size could be time-consuming and impractical, while automatic adjustment mechanisms may introduce additional complexity or instability.

While the LMS and Leaky LMS algorithms are designed to handle a broad range of noise types, they are not always optimal for highly structured or periodic interference, such as electrical hums or constant mechanical noise. The method may struggle to suppress these specific types of noise without additional filtering mechanisms. Furthermore, the performance of the adaptive filter can degrade if the noise profile is not sufficiently modeled or if it significantly overlaps with the frequencies of the PCG signal itself.

3.7 Engineering Standards

IEEE Standard 610.12-1990 (Standard Glossary of Software Engineering Terminology): This standard provides definitions and terminology used in the field of software engineering, including signal processing. It is critical for ensuring that the terminology used in describing adaptive filters and signal processing techniques like LMS and Leaky LMS is consistent and aligns with established practices in the field.

IEEE 2700-2018 (Standard for Digital Signal Processing (DSP) Algorithms):
This standard outlines the requirements for digital signal processing algorithms, which includes those used for adaptive filtering. It covers aspects like performance, accuracy, and the general principles to follow when designing algorithms for processing signals such as PCG. Adhering to this standard ensures the algorithms meet certain accuracy and stability criteria when used for medical applications.

CHAPTER 4

Design and Methodology

4.1 Theoretical Analysis

(4.1.1) Module:

(i) Adaptive Filtering:

The goal of adaptive filtering systems is to minimise noise while preserving the intended signal. To counteract the noise effect on voice signal propagation, digital filters such as IIR and FIR are practical filtration techniques. The advancement of these digital filters has led to the adoption of adaptive filters. Through the use of a feedback mechanism, the closed-loop adaptive filter improves its transfer function. They readily adjust to the conditions of the environment in which they are utilised. Among the factors that be adjusted are the length, step size, and coefficients.

The adaptive algorithm operates in two steps. The first phase is filtering, where input is filtered to produce the output in the standard manner. The second stage, sometimes referred to as the adaption weighting phase, compares the output of the filtering section with the predicted output. The error signal that is obtained is then sent back to the controller in order to update the weights.

(ii) Least Mean Square Algorithm:

A popular adaptive filtering method in machine learning and digital signal processing is the Least Mean Square (LMS) algorithm. By repeatedly modifying the filter parameters, it reduces the mean square error between the estimated and the intended output signals. The LMS algorithm provides immediate processing and flexibility in response to changing conditions, allowing for maximum performance in systems with uncertain or time-varying input data. In several domains, including automation, algorithms for learning, and signal processing, the Least Mean Square (LMS) Algorithm is a crucial and popular adaptive filtering method.

(iii) Noise Cancellation:

The technique of removing an associated benchmark signal from the primary signal to reduce or eliminate unwanted noise or interference is known as noise cancellation. This method is widely used in various applications, including enhancing phonocardiogram (PCG) signals by suppressing background noise and improving speech signals by eliminating environmental disturbances. In PCG analysis, noise cancellation helps in accurately detecting heart sounds by filtering out artifacts such as lung sounds or muscle noise. Similarly, in speech processing, it improves intelligibility by reducing ambient noise, ensuring clearer communication and more effective automated speech recognition.

(IV) Phonocardiogram (PCG) Signal:

Phonocardiography is the recording of all the sounds produced by the heart in its cardiac cycle. A phonocardiogram (also known as a PCG) is a projection of high-fidelity capture of the noises and murmurs created by the heart with the use of a device called a phonocardiograph. Cardiovascular diseases are the major root cause of death worldwide. Given the current circumstances, a precise approach is required to ascertain whether an individual's heartbeat and heart signals are irregular. In contemporary medicine, phonocardiograms (PCG) are methods for detecting cardiovascular anomalies.

(V) Leaky LMS Algorithm:

The Leaky Least Mean Squares (Leaky LMS) algorithm is a variation of the LMS adaptive filtering algorithm that incorporates a small "leakage" factor to improve stability and reduce the risk of divergence. This leakage allows the algorithm to retain a memory of past values, which helps in managing parameter drift. Leaky LMS is commonly used in applications such as noise cancellation, system identification, and adaptive filtering, where maintaining steady performance over time is critical, especially in environments with changing conditions or noise. It is also widely used in speech enhancement and PCG signal processing, where it helps to improve signal clarity and reduce interference.

(4.1.2) Methodology:

(I) The LMS Algorithm Methodology:

We developed the following relations using the descent LMS method:

$$\nabla_w J[n] = -2p_{dx} + 2Rw(n)$$

The simplest choices of the estimators Rx and dx are the instantaneous estimates defined by

$$R \approx x(n)x^T(n) \quad \text{and} \quad p_{dx} \approx d(n)x(n)$$

Substituting the above values in (2) and then combining (1) and (2), we obtain

$$w(n+1) = w(n) + 2\mu x(n)[d(n) - w^T(n)x(n)]$$

Or,

$$w(n+1) = w(n) + 2\mu e(n)x(n)$$

Where

$$y(n) = w^T(n)x(n) \quad \text{(Filter output)}$$

And

$$e(n) = d(n) - y(n) \quad \text{(Error)}$$

The algorithms defined constitute the LMS algorithm. The algorithm at each iteration requires that x(n),d(n), and w(n) are known. The LMS algorithm is a stochastic gradient algorithm if the input signal is a stochastic process. This results in varying the pointing direction of the coefficient vector during the iteration. An FIR adaptive filter realization is shown in the equations of the LMS filter. Where

$$w(n) = [w_0(n), w_1(n), \dots, w_{M-1}(n)]^T$$

Are the filter coefficients and the input data is

$$x(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T$$

(II) Recursive Leaky LMS Algorithm:

Initial conditions**:**

Clean Speech Signal: $s(n)$

Noise Signal: $v(n)$

Composite Noisy Signal:$d_1(n) = s(n) + v(n)$

Reference Noise Signal: $x_1(n) = v'(n)$

Step-size: μ

Leakage Coefficient: γ, where $0 < \gamma < 1$

Stage 1 – First LLMS Filter

Inputs:

Primary Signal:

$$d_1(n) = s(n) + v(n)$$

Reference Signal:

$$x_1(n) = v'(n)$$

Filter Output:

$$y_1(n) = w_1^{\mathrm{T}}(n)\, x_1(n) = \hat{v}(n)$$

Error Signal:

$$e_1(n) = d_1(n) - y_1(n) = s(n) + v(n) - \hat{v}(n) = s(n) + \Delta v(n)$$

Weight Update (Leaky LMS):

$$w_1(n+1) = (1 - \mu\gamma)\, w_1(n) + \mu\, e_1(n)\, x_1(n)$$

$$= (1 - \mu\gamma)\, w_1(n) + \mu\, [d_1(n) - x_1^{\mathrm{T}}(n)\, w_1(n)]\, x_1(n)$$

Stage 2 – Residual Noise Estimation

Inputs:

$$d_2(n) = e^1(n) = s(n) + \Delta v(n)$$

$$x_2(n) = x_1(n) - y_1(n) = \Delta v'(n)$$

Output:

$$y_2(n) = w_2{}^{\mathrm{T}}(n)\, x_2(n) = \Delta \hat{v}(n)$$

Error Signal:

$$e_2(n) = d_2(n) - y_2(n) = s(n) + \Delta v(n) - \Delta \hat{v}(n) \approx s(n)$$

Weight Updates:

$$w_2(n + 1) = (1 - \mu\gamma)\, w_2(n) + \mu\, e_2(n)\, x_2(n)$$

Stage M – Final Stage (Recursive Structure)

Inputs:

$$d_M(n) = e_{M-1}(n) = s(n) + \rho v(n)$$

$$x(n) = x_1(n) - y_{M-1}(n) = s(n) + \rho v'(n)$$

Output:

$$y_{\mathrm{m}}(n) = w_{\mathrm{m}}{}^{\mathrm{T}}(n)\, x_{\mathrm{m}}(n) = \rho\, \hat{v}(n)$$

Error Signal:

$$e_{\mathrm{m}}(n) = d_{\mathrm{m}}(n) - y_{\mathrm{m}}(n) = s(n) + \rho\, v(n) - \rho\, \hat{v}(n) \approx s(n)$$

(III) The Proposed Switched Adaptive Methodology:

The signal with noise, denoted as d(m) constitutes the primary input signal directed to the ANC

$$d_1(m) = s(m) + p(m)$$

the signal supplied to the filter, $x1(m)$, is associated with the noise signal over time $p(m)$. An exact copy of the noise signal is created by the adaptive filter and is indicated by

$$x_1(m) = p'(m)$$

Regarding the initial stage, the results obtained through the utilization of the LLMS algorithm are expressed as follows:

$$e_1(m) = d_1(m) - y_1(m)$$

where

$$y_1(m)w(m+1) = (1-\mu\gamma)w(m) + \mu e_1(m)x_1(m)$$

The updating of weights occurs in the following manner:

$$w(m+1) = (1-\mu\gamma)w(m) + \mu e_1(m)x_1(m)$$

where γ is the leakage factor introduced. When the leakage coefficient is introduced, any undamped modes are forced to zero, and any filter coefficients that are present are also forced to zero if either $e1(m)$ or $x1(m)$ is zero. µLLMS is the step-size of LLMS filter. Equations (1) and (4) can be substituted in (3) to obtain

$$(1-\mu\gamma)w(m) + \mu[d_1(m) - x_T(m)w(m)]x(m)$$

& $$e_{1LLMS}(m) = s(m) + p(m) - \hat{p}(m)$$

Similarly, the following are the output parameters determined by the LMS algorithm

$$y_1(m) = w_1^T(m)x_1(m) = w_1^T(m)p'(m) = \hat{p}(m)$$

The updated weights are given by

$$w_1(m+1) = w_1(m) + \mu e_1(m)p'(m)$$

The next stage aims to eliminate the noise $\Delta p(m)$ from $d2(m)$.Therefore, it is necessary to employ a signal that is correlated with $\Delta p(m)$ as the reference input or the secondary input signal to the filter.It is given by:

$$x_2(m) = x_1(m) - y_1(m) = p'(m) - \hat{p}(m) = \Delta p'(m)$$

The subsequent stage ANC's inputs are:

$$d_2(m) = e_1(m) = d_1(m) - \hat{p}(m) = s(m) + \Delta p(m)$$

$\Delta p'(m)$ exhibits a correlation with $\Delta p(m)$.As a result, it proves to be more effective in noise reduction. The control switch also plays a role in choosing an appropriate algorithm for the second stage, and this sequence repeats as more stages are incorporated.

The specialty of the LLMS is the leakage factor which quickly responds to sudden changes in the input signal while retaining some memory of past updates, enhancing its responsiveness also Leaky LMS algorithm can offer better stability, especially when dealing with noisy or ill-conditioned input signals of the PCG signal.

(IV) Block Diagram:

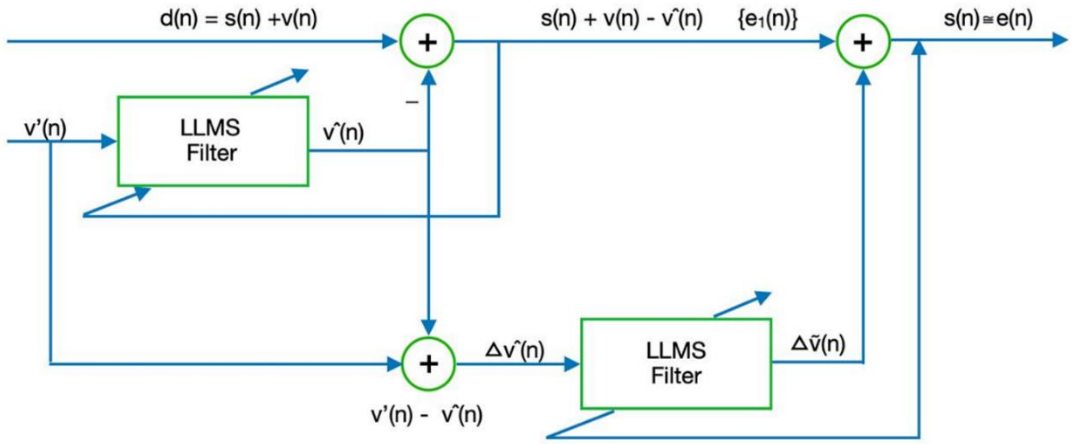


Fig 1 Proposed 2-stage Leaky LMS Adaptive Filter

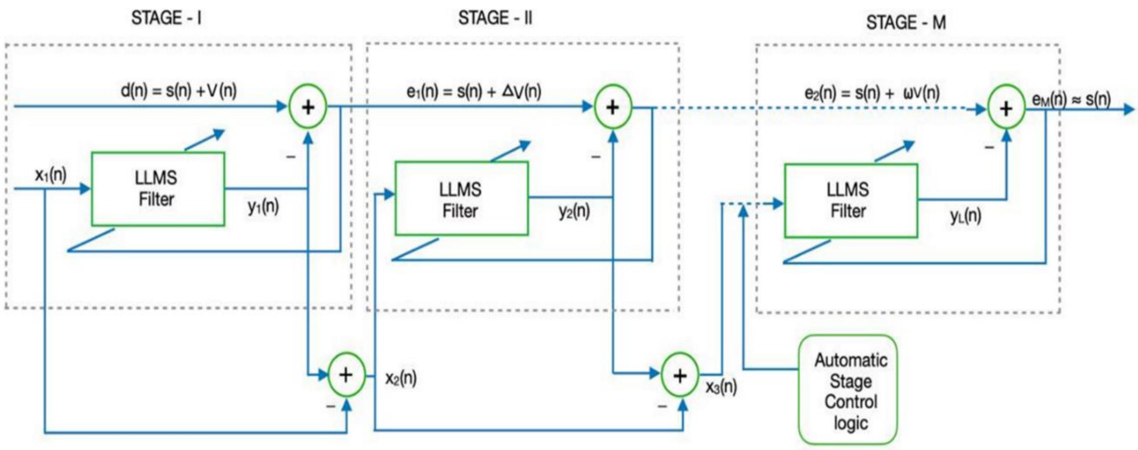


Fig 2: Proposed Multi-stage Leaky LMS Adaptive Filter

4.2 Description of system environment:

This project uses a PCG (Phonocardiogram) signal and MATLAB software to perform LMS (Least Mean Square) adaptive filtering. The MATLAB R2024a platform is part of the system environment, which runs on a 64-bit, standard Windows 10+ operating system.

4.3 Design Specifications:

4.3.1 Hardware Required:

- Processor: Intel i5+(2.5 GHz).
- Memory: Minimum 4GB RAM
- Storage: Required to access MATLAB files.

4.3.2 Software Required:

The LMS Adaptive Filtering project on PCG signals requires hardware and software for good performance:
Like MATLAB R2024a or later: essential program for data analysis and algorithm development.
Signal Processing Toolbox: For preprocessing and analysing PCG signals.
The LMS algorithm is one of the specialised adaptive filtering features offered by the DSP System Toolbox.
Data Files: PCG signals to be fed into the filtering algorithm in WAV or MAT formats.
Operating System: Windows 10 +(64-bit)

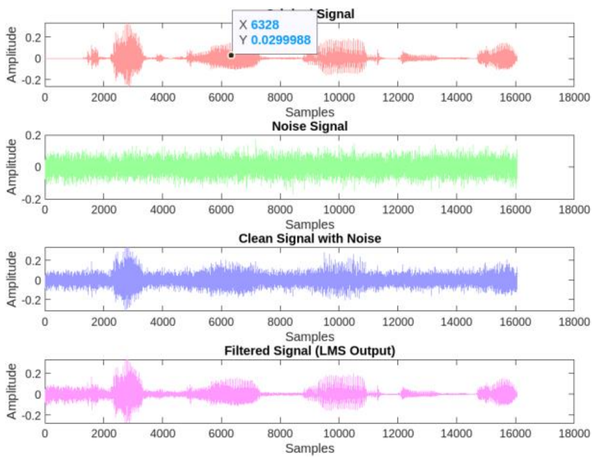
CHAPTER 5

Results and Discussion:

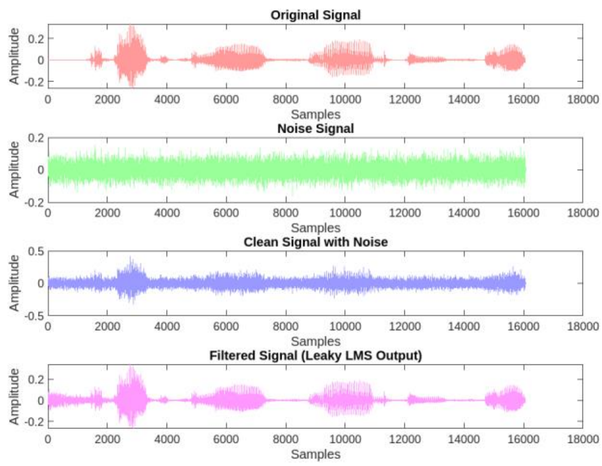
5.1 Experimental Results:

The proposed filter's ability to reduce noise in both speech and PCG signals affected by external interference has been carefully tested. Figure 1 highlights the denoising performance of the multi-stage Leaky LMS filter, showing how well it recovers a clean signal from a noisy one. The results confirm that the filter's output closely matches the original clean signal, proving its ability to reduce unwanted noise in both types of signals. The multi-stage Leaky LMS switching method effectively separates and removes noise, ultimately restoring the speech and PCG signals. The graphical results are shown below.

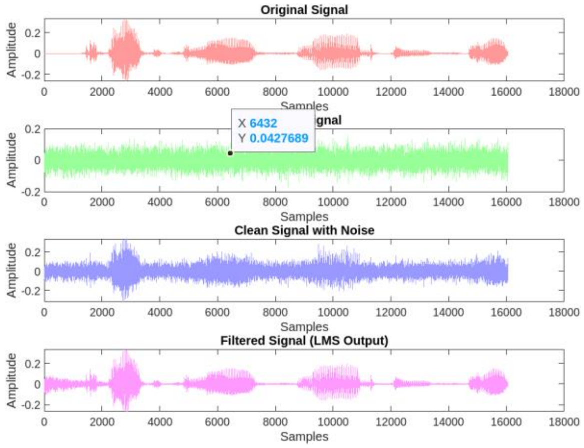
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1



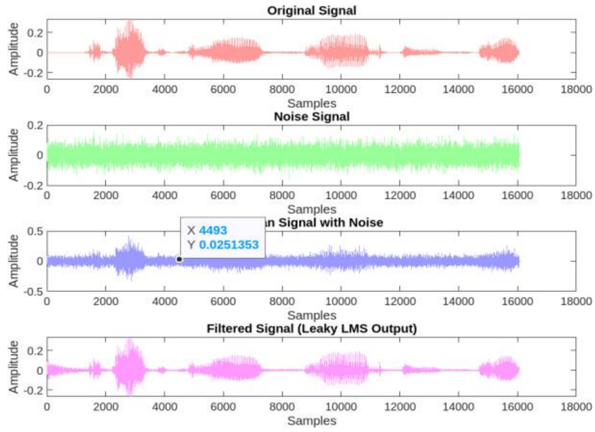
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1



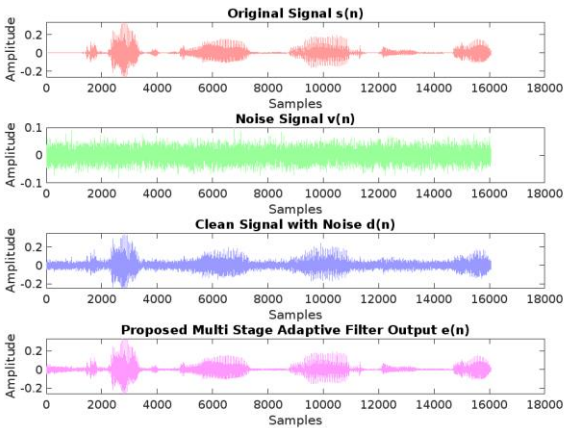
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 2



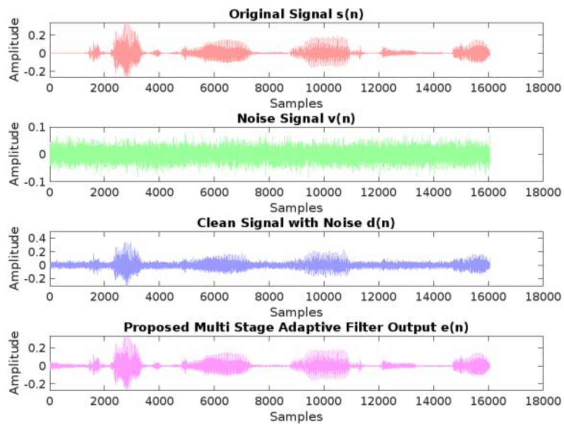
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 2



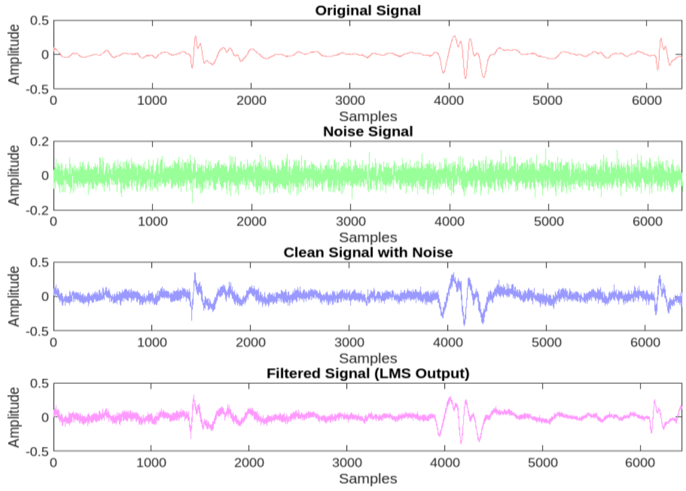
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 3



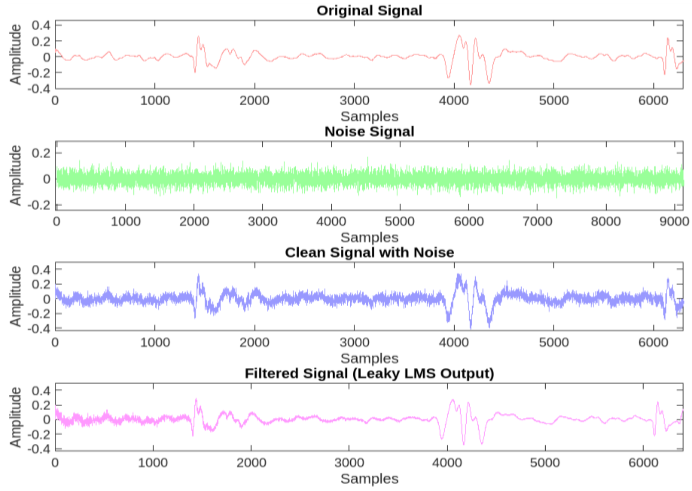
SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 3



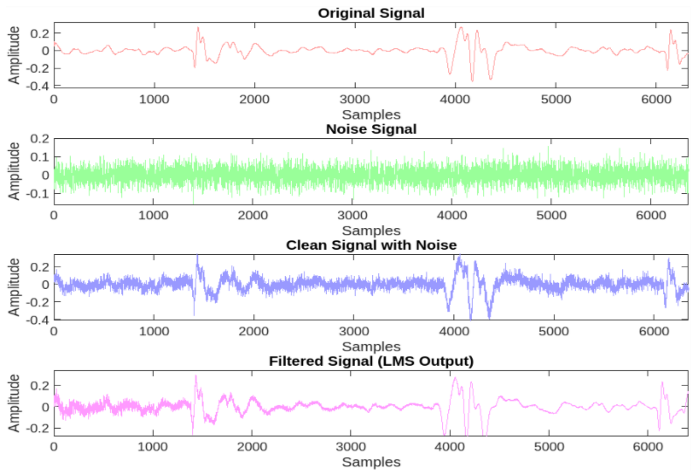
PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1



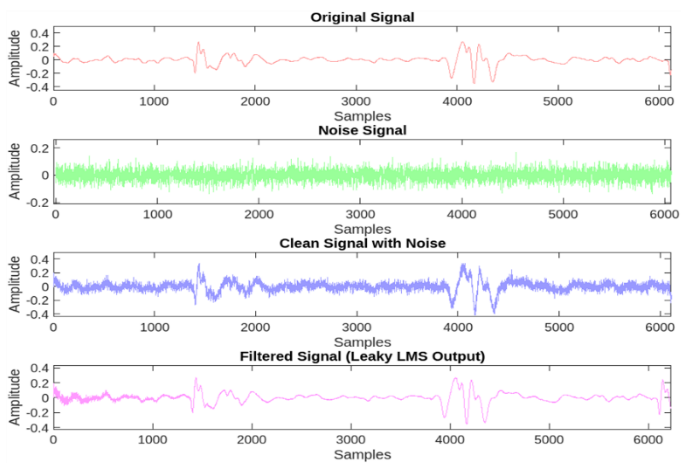
PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1



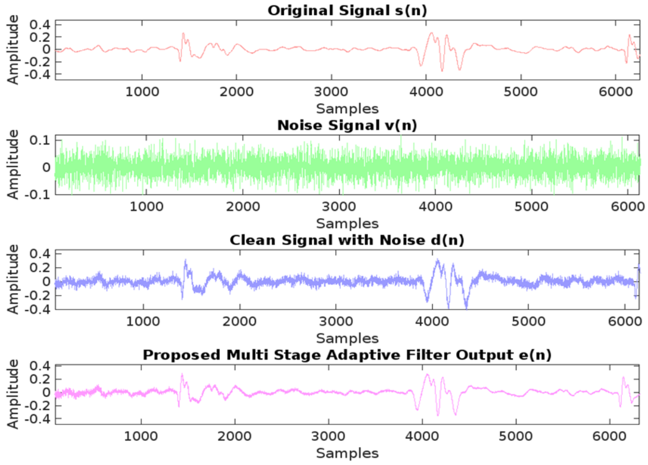
PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 2



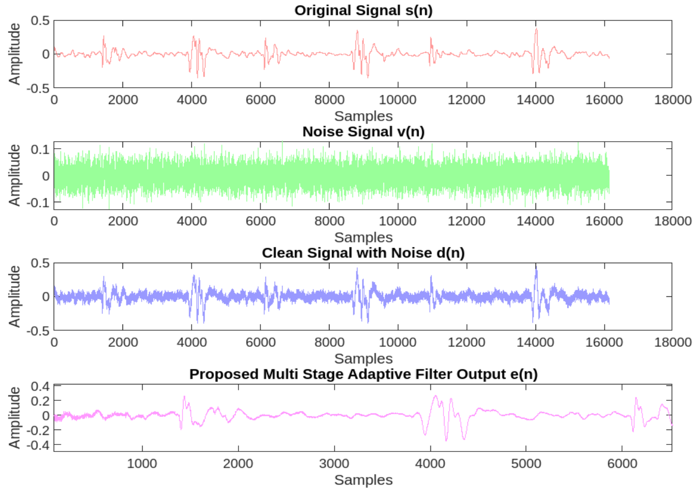
PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 2



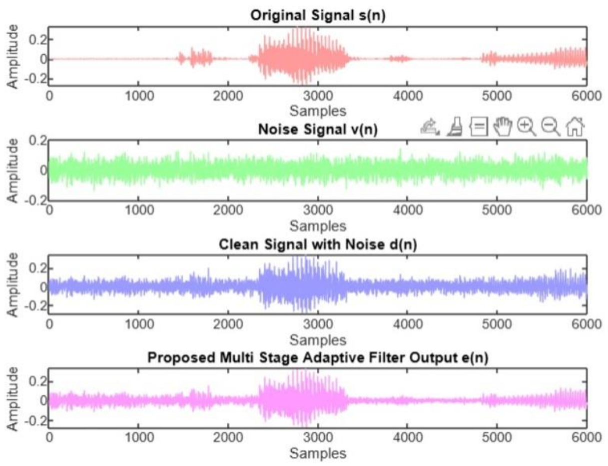
PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 3



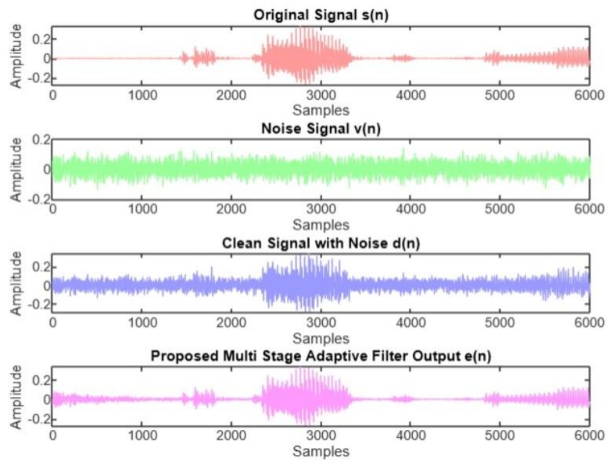
PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 3



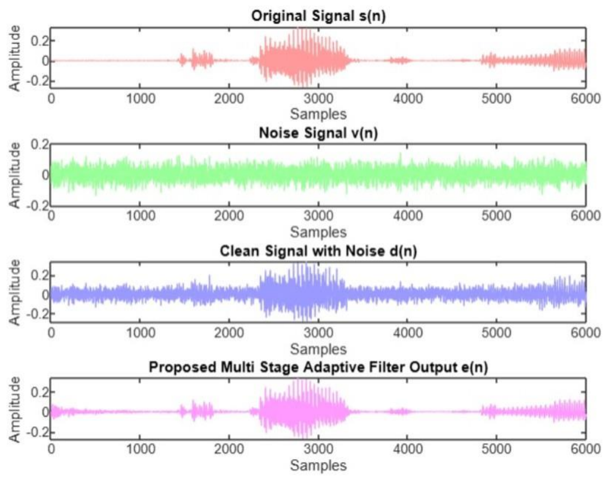
SPEECH SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 1



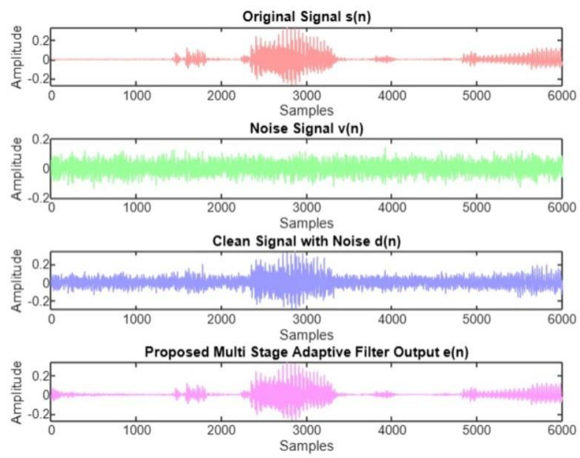
SPEECH SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 2



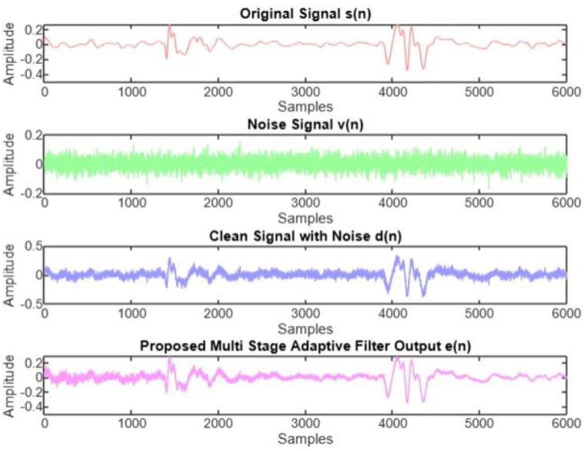
SPEECH SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 3



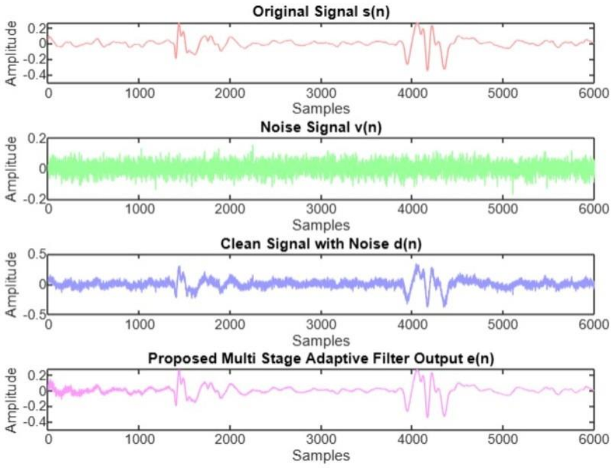
SPEECH SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 4



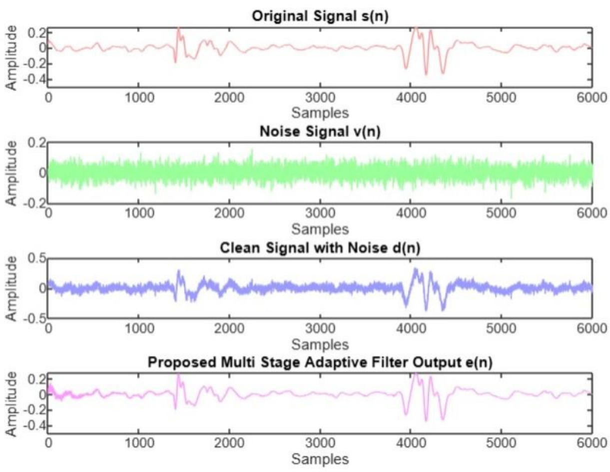
PCG SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 1



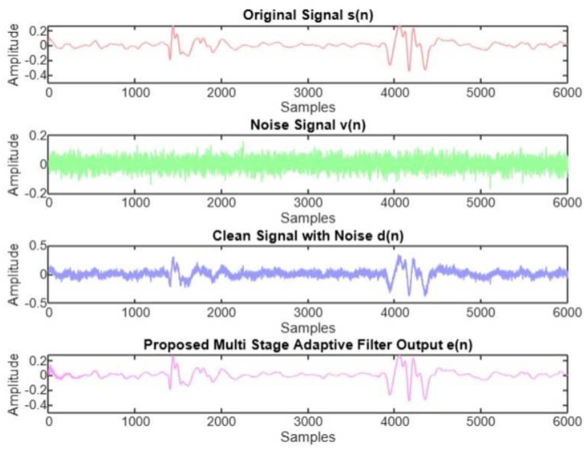
PCG SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 2



PCG SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 3



PCG SIGNAL WITH GAUSSIAN NOISE USING RECURSIVE LEAKY LMS STAGE 4



Results for Speech signals with added Gaussian noise using LEAKY LMS Adaptive Filter
Input SNR: 5 dB

STAGE NUMBER	MSE	SNR	CORRELATION COEFFICIENT
Stage 1	0.00010871	20.2909 dB	0.10078
Stage 2	8.199e-05	21.2149 dB	0.092204
Stage 3	3.452e-06	27.4779 dB	0.029336
Stage 4	6.4288e-06	31.3624 dB	0.029206

Results for PCG signals with added Gaussian noise using LEAKY LMS Adaptive Filter
Input SNR: 5 dB

STAGE NUMBER	MSE	SNR	CORRELATION COEFFICIENT
Stage 1	0.00011662	17.3809 dB	0.13525
Stage 2	6.1511e-05	19.553 dB	0.10459
Stage 3	1.8372e-05	24.3425 dB	0.055864
Stage 4	7.1978e-06	28.3122 dB	0.030841

Results for Speech signals with added Gaussian noise using RECURSIVE LEAKY LMS Adaptive Filter Input SNR: 5 dB

STAGE NUMBER	MSE	SNR	CORRELATION COEFFICIENT
Stage 1	0.00017067	11.2235 dB	0.25905
Stage 2	3.4712e-05	16.7027 dB	0.14027
Stage 3	1.8189e-05	19.3341 dB	0.10263
Stage 4	1.0313e-05	21.7174 dB	0.076304

Results for PCG signals with added Gaussian noise using RECURSIVE LEAKY LMS Adaptive Filter
Input SNR: 5 dB

STAGE NUMBER	MSE	SNR	CORRELATION COEFFICIENT
Stage 1	0.0015206	14.2807 dB	0.13098
Stage 2	6.2058e-05	19.5229 dB	0.10299
Stage 3	2.0867e-05	23.8127 dB	0.061437
Stage 4	1.0072e-05	26.8651 dB	0.039851

5.4 Conclusion:

In this study, we introduced a multi-stage adaptive filtering method using the Leaky LMS (LLMS) algorithm to reduce noise in both speech and Phonocardiogram (PCG) signals. The results show that this approach effectively removes noise while keeping the original signal clear. By using LLMS in multiple stages, the system adapts to different noise levels, making it suitable for real-world applications where noise keeps changing.

One of the main benefits of this method is its ability to reduce noise without affecting the signal quality too much. Traditional filters often struggle with this—either removing too much and distorting the signal or not removing enough and leaving noise behind. The multi-stage LLMS approach avoids these problems by gradually refining the signal in steps, leading to better results.

This method is also cost-effective and does not require too much processing power. Unlike complex filtering techniques that need heavy computation, the multi-stage LLMS approach remains efficient while still providing high-quality results. This makes it useful for real-time applications like improving speech in phone calls and reducing noise in PCG signals for medical use.

The study highlights how adaptive filtering can improve signal quality in noisy conditions. The improvements in clarity and noise reduction suggest that multi-stage LLMS filtering could be a good solution for practical applications, including biomedical signal processing and speech communication. Future research can focus on fine-tuning the filter settings for different types of signals and expanding its use in other areas of signal processing.

Overall, this research shows the importance of adaptive filtering in real-world situations and establishes multi-stage LLMS as an effective and efficient way to reduce noise in speech and PCG signals. The findings open up possibilities for further advancements in signal processing, ensuring that important information is preserved while unwanted noise is minimized.

5.5 Future Enhancement:

To further improve noise reduction while keeping signal integrity, future studies may explore more effective recursive multi-stage Leaky LMS (LLMS) filtering algorithms. The system can attain quicker convergence and more ability to changing noise conditions by simplifying the recursive filtering process. The approach can be made more robust by implementing advanced parameter tuning methods, such as machine learning-based optimization, which can help constantly respond the filter coefficients for various signal types. Furthermore, introducing this method into edge computing devices and real-time embedded systems may allow for low-power, high-performance noise reduction for speech processing, technology, and healthcare applications. While maintaining the approach's calculation efficiency and adaptability to a variety of real-world settings, these developments will contribute to an improvement in signal clarity.

REFERENCES

1. H. Deng and M. Doroslovacki, "A New Adaptive Noise Cancellation Scheme for Speech Enhancement," IEEE Transactions on Signal Processing, vol. 53, no. 7, pp. 2341-2351, July 2005.

2. Yang Liu, A Noise Reduction Method Based on LMS Adaptive Filter of Audio Signals, 3rd International Conference on Multimedia Technology, ICMT, 2013.

3. S. Shahidi and M. Mirzaei, "Performance Analysis of Adaptive Filters for Noise Cancellation in Various Environments," IEEE Transactions on Signal Processing, vol. 54, no. 8, pp. 2952-2962, Aug. 2006, doi: 10.1109/TSP.2006.870888.

4. Sayed A.H.: Fundamentals of adaptive Filtering. First Edition. Wiley Interscience, (2003).

5.Maurya, A.K.: Cascade-cascade Least Mean Square LMS Adaptive Noise Cancellation. Cir-cuits Syst. Signal Process. 37(9), 3785-3926 (2018).

6.Pauline, S.H., Dhanalakshmi, S.: A low-cost automatic switched adaptive filtering technique for denoising impaired speech signals. Multidimensional Systems and Signal Processing 33, 1387-1408 (2022).