18ECP109L – PROJECT

LEAKY LMS BASED LOW COMPLEXITY ADAPTIVE NOISE CANCELLATION

A PROJECT REPORT

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ABSTRACT

Phonocardiogram (PCG) signals are acoustic recordings that capture the complex sounds generated by the heart, commonly obtained using a stethoscope. These recordings are essential in revealing details of the heart's mechanical actions. By analyzing PCG signals healthcare providers can accurately identify heart-related conditions. However, PCG signals are often disrupted by noise from surrounding environmental sounds, which can compromise the precision of analysis. This interference causes diagnostic errors or missed conditions. To ensure the accurate diagnosis, denoising the PCG signal is necessary. Leaky LMS is a variant of LMS algorithm where Leaky factor is introduced. This project presents the design proposal of the Multistage Leaky LMS algorithm enhancing stability and making it low complex design which offers improved performance, exhibiting a higher Signal-to-Noise Ratio (SNR) and reduced Mean Squared Error (MSE). The Multistage Leaky LMS filter is ideal for applications like speech enhancement and other real time acoustic signals.

Sustainable Development Goals:

This project is best aligned with the United Nations Sustainable Development Goal (SDG) 3: Good Health and Well-being, through the improvement of medical diagnostic quality and reliability by utilizing advanced signal denoising methods. It is also aligned with SDG 9: Industry, Innovation, and Infrastructure, through the inducement of innovation in medical technology and the attainment of the development of smarter, more efficient diagnostic tools for telehealth and remote health monitoring, ultimately enhancing health outcomes and decreasing healthcare disparities.

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LIST OF SYMBOLS & ABBREVIATIONS

PCG:	Phonocardiogram
LMS:	Least Mean Squares
LLMS:	Leaky Least Mean Squares
ANC:	Adaptive Noise Cancellation

CHAPTER 1

INTRODUCTION

1.1 Phonocardiogram Signals:

Phonocardiogram (PCG) recordings are a must for heart diagnostics and are based on capturing the sound signals that the heart gives out in its work. These sounds are created by the opening and closing of the heart valves, as well as the blood going through the heart's chambers. When these acoustic patterns are analyzed, clinicians can discover much more about the functioning of the heart. PCG recordings are especially helpful in finding the early symptoms of heart problems, such as the presence of unusual heart murmurs, the occurrence of arrhythmias of the heart, and valve malfunctions. However, in medical settings, external background noise in PCG recordings may obscure important heart sounds like those generated by valve activity hindering doctors from properly diagnosing heart conditions or misdiagnosing the conditions. Hence, denoising of this PCG signals is crucial before further analysis.

1.2 Speech Signals:

The analysis of speech signals can lead to an early diagnosis of several diseases, when a person's speech is being monitored for any changes in tone, articulation, and fluency. Just like acoustic signals of the heart can indicate underlying cardiovascular disease, the sounds of speech can also act as valuable biomarkers for other diseases. It is normal that slight changes in speech are the first things that can be recognized as signs of certain disorders such as neurological, cognitive, and respiratory ones. Thus, in the case of Parkinson's disease, the most common symptoms at the initial stage are a low voice, a monotonous speech, and slurred articulation. Correspondingly, patients with Alzheimer's disease may not only experience word retrieval difficulties but also have stops, or their speech patterns will be fragmental. One of the symptoms of a stroke can be a person's speech that suddenly becomes blurred or incoherent, which usually is a strong warning sign. But to be able to detect these early symptoms, the speech signals need to be free from background noise interference. Hence, to maintain the reliability of these signals, it is essential to implement advanced noise reduction and enhancement techniques, enabling precise medical assessments and seamless communication.

1.3 Adaptive Noise Cancellation:

Adaptive Noise Cancellation (ANC) is a signal processing procedure of reducing intercept signals' noise by presenting a reference noise signal and utilizing adaptive filtering algorithms. While typical filters are unchanged, ANC changes its filter continually and does it in real-time considering the changes of the ambient, which makes it very efficient in dynamic and unpredictable situations. It has been established to be particularly helpful in scenarios where a clear signal is of utmost importance, such as in medical diagnostics (e.g., denoising PCG or speech signals). The intervention that ANC provides, i.e., reduction of noise without affecting signal quality, is beneficial in a significant manner not only in accuracy but also in reliability of noisy-environment operating systems.

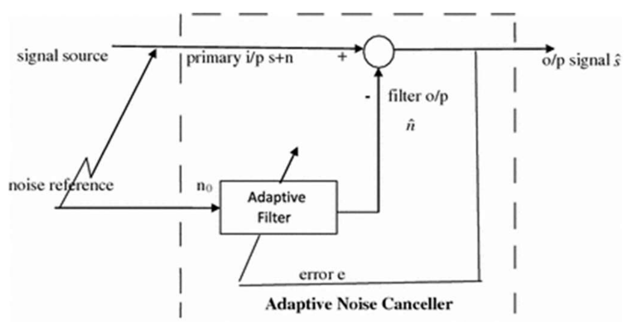

Figure 1.3.1 Schematic diagram of Adaptive Filter

The adaptive filter in Figure 1.3.1 represents a basic structure of the adaptive filter with primary input signal is $s + n$, where s represents the signal without noise and n represents the noise. Secondary input is the reference noise signal n_o which results in the error signal and filter output $\hat{n}$.

In this study we use Multistage Leaky LMS Adaptive Filtering technique which is a variant of LMS adaptive filtering technique.

CHAPTER 2

LITERATURE SURVEY

Noise interference remains a significant challenge, particularly due to its adverse effects on both signal integrity and human well-being especially for individuals exposed to prolonged noisy environments. Accurate diagnosis of impaired speech relies heavily on clean, noise-free signals, while PCG (Phonocardiogram) signals, being especially susceptible to external disturbances, also require thorough noise removal prior to analysis. Numerous denoising methods have been explored in the literature to improve quality of both PCG and speech signals. Broadly, the research can be categorized into development of adaptive noise cancellation systems, exploration of adaptive filtering algorithms, techniques for speech signal enhancement, and methods for PCG signal denoising.

Dixit et al. introduced a feedback-connected cascaded LMS adaptive filter aimed at reducing hardware complexity while maintaining effective noise cancellation. Their study highlights that structural parameters, including cascade stages and feedback configuration, significantly influence filter performance, underscoring the importance of architectural optimization in resource-constrained applications.

Yang et al. presented an LMS adaptive filter-based noise reduction technique to cater to audio signals. The designed scheme in the paper primarily relied on the adaptive nature of the LMS algorithm to strike the noise component off audio inputs. The method can be a good solution for very flexible audio environments because of its ability to reduce both stationary and non-stationary noise. Their experimental work uncovered a big benefit of the LMS-based noise reduction method: it truly improves audio signal quality through the reduction of distortion while featuring the original sound characteristics.

Lu et al. introduced the Diffusion Leaky LMS (DLLMS) algorithm to solve distributed estimation problems in a network. The proposed algorithm improves numerical stability and reduces misadjustment, making it more effective in real-time applications. By incorporating a leaky factor, the DLLMS algorithm enhances the convergence rate and stability of distributed systems, leading to better performance in scenarios where data is processed across multiple nodes or agents.

Raut et al. have described a technique of adaptive noise cancellation by the use of the Least Mean Square (LMS) filter algorithm to minimize noise in audio signals. In the work, the LMS algorithm is simulated in MATLAB to eliminate noise in a way that the signal quality is restored and the desired audio output is obtained. The paper highlights the simplicity and efficiency of the LMS algorithm in adaptive filtering applications, making it suitable for real-time noise cancellation systems. The authors also emphasize the practical application of the method in various engineering fields where noise suppression is crucial.

Sharma et al. proposed an enhanced version of the Normalized Least Mean Square algorithm for adaptive noise cancellation. The modified LMS algorithm demonstrates improved convergence rates and enhanced noise reduction capabilities compared to traditional methods. The modification embraces better noise absorption by adjusting the LMS algorithm to be the most effective in places with an unstable noise level. The study is an indication that the new LMS algorithm is still the best choice for real-time noise cancellation because it enhances robustness and efficiency moreover it outperforms the overall performance of the signal processing task.

Lee et al. implemented a study simulating applications of LMS adaptive filtering for noise cancellation. The simulation demonstrated the effectiveness of LMS filters in reducing unwanted noise from speech signals, showcasing their ability to improve speech clarity in noisy environments. The results highlighted the potential of LMS adaptive filters as a practical solution for real-time noise reduction, particularly in audio and speech processing applications where preserving the quality of the original signal is essential.

Dixit et al. provided a comprehensive review of various LMS-based adaptive filter algorithms, including leaky LMS variants, for noise cancellation applications. The paper discusses the strengths and limitations of these algorithms in different noise environments, emphasizing their adaptability and performance in real-time noise reduction tasks. The review highlights advancements in LMS algorithms, particularly the leaky LMS, which enhances convergence speed and stability. The authors also explore the applications of these adaptive filters in diverse fields, including audio processing, communication systems, and signal enhancement.

Shukor et al. presented a multi-stage cascaded adaptive filter architecture which deployed the Sign Error Least Mean Square (SELMS) algorithm to facilitate the noise suppression in the phonocardiogram (PCG) signals. The system that was proposed made use of several adaptive filter stages with different counts, which were automatically changed by the signal's correlation coefficient, to handle the convergence speed and the steady-state mean square error. The results of simulation showed that the model provided an 8–10 dB higher Signal-to-Noise Ratio (SNR) in Gaussian noise conditions and a 2–3 dB higher SNR when there is colored noise present, as compared to the similar cascaded LMS filter models. Also, for the issue of Gaussian noise, the Peak Signal-to-Noise Ratio (PSNR) increased up to 7 dB, while in pink noise a 1–2 dB increase was observed. The SELMS-based method gives a simple solution for PCG signal denoising, which in reality is used in real-time.

Ali et al. conducted a study to discuss the utilization of Least Mean Square (LMS) as well as Normalized Least Mean Square (NLMS) algorithms for elimination of noise in phonocardiogram (PCG) signals. The work revolves around extending of these adaptive filtering paradigms in the noise cancellations of PCG signals to the point where the noise-type variety is brought down to the minimum. The comparison of LMS and NLMS algorithms is founded on the underlying aspects of speed of convergence, steadiness, and effectiveness of noise reduction. The via simulated results have shown that the NLMS algorithm is a better performer than the LMS algorithm in case of variable noise levels, providing space for better adaptability and offering a faster convergence. It has been concluded that the NLMS-based filters are the best candidates for the PCG signal processing in real-time, throughout the noisy environment as they provide a sensible approach for the medical diagnostics with the help of noise reduction.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Problem Statement:

One of the major challenges in medical diagnostics and communication systems is the speech signal distortion that is created by noise interference. The sources of environmental background noise can be broadly classified into crowded places, urban landscapes, and a variety of transmission media, whose interference with the speech makes it unintelligible to the human ear and automatic recognition systems. In speech-based disease diagnostics of dysphonia and Parkinson's disease, the noise as a contaminant might be misunderstood, hence the incorrect diagnostics will halt the early determination and fluctuate the treatment processes. The presence of noise in the speech recognition systems also decreases their reliability and hence their healthcare and communication sectors' efficiency are compromised. Given these issues, it is necessary to look into the development of innovative noise reduction methods for higher levels of clarity in speech, diagnostic results, and the performance of automatic speech processing systems.

3.2 Challenges in signal processing:

The main problems in speech signal processing are caused by the background noise and channel distortions that degrade the speech signal intelligibility. The noise, in this case, may be a result of various sounds in the environment which in effect introduces into the intended speech other non-relevant factors. Also, the channel distortions of the communication system may additionally change the frequency or amplitude of the speech signal, thus contributing to the complexity of the process. In this way, successful speech processing will be contingent on the development of such noise suppression systems that do not reduce the quality of sound but that mostly handle speech intelligibility.

3.3 Existing solutions:

Existing methods of noise reduction in speech signals include methods like wavelet transforms, deep learning models, and empirical mode decomposition (EMD). These methods have documented varying degrees of success in the removal of unwanted noise from speech signals, but all of them are computationally complex.

- Deep learning models, particularly neural network-based, are capable of learning to adjust to complex and dynamic patterns of noise, often documenting significant results in noise reduction and speech enhancement.
- Wavelet transforms provide a good match for non-stationary noise reduction as they are capable of discovering signals at different scales by which they can capture both transient high-frequency details and low-frequency components. The multi-resolution property of wavelets leads to the capability to handle time-varying signals like Phonocardiogram (PCG) signals. These signals represent dynamic characteristics. Noise that is held at both time and frequency domains with wavelets gives them an advantage over traditional methods such as the Fourier transforms. But, the computational complexity might be a problem. It's particularly the case when dealing with larger signals or real-time systems because it involves several passes and a significant amount of memory. Furthermore, the proper wavelet function and decomposition level need to be found, which can be a trial and error process. Moreover, wavelet transforms can also be affected by edge effects giving the results of distortions at signal boundaries, and the use of them in real-time applications has a direct dependency of processing power and memory capacity.
- EMD is another method that breaks down signals into intrinsic mode functions, allowing for the removal of noise and retention of the characteristic features of speech. These methods, however, have large computational overhead, with enormous amounts of processing resources and time being needed for execution. They are thus not well-suited for applications that involve real-time processing, where low-latency performance is needed. Despite their efficiency, these solutions are difficult in implementation, particularly in systems that need efficient and timely execution, such as mobile or embedded systems that need real-time processing of speech signals.

3.4 Proposed solution:

The multistage Leaky Least Mean Squares (LLMS) adaptive filter algorithm is an appropriate algorithm for noise cancellation from speech and phonocardiogram (PCG) signals. The specific algorithm is noted for its simplicity and low computational cost, and it is an appropriate for applications in real-time processing.

Among the primary advantages of the Leaky LMS approach is that it can easily achieve fast convergence while successfully filtering out noise even in unstable and non-stationary environments. The presence of a "leakage" factor in this algorithm prevents stability problems in long-term filtering and ensures that key features of the signal are not lost. For speech signals, this means easier and more comprehendible speech despite the presence of ambient noise. For PCG signals it helps in better detection of important cardiac events such as valve movement and heartbeats, which may otherwise be undetectable due to ambient noise. Using a multistage filter approach, the enhanced version of the Leaky LMS algorithm is further provided with increased flexibility, sequentially enhancing the signal while ensuring maximum reduction of noise. This technique delivers a well-tuned solution ensuring minimal noise and is computationally efficient, a perfect algorithm for real-time processing in both diagnostic medicine and communications technology.

3.5 Scope of Study:

The current study focuses on using the Multistage Leaky LMS (LLMS) algorithm to reduce noise in speech and PCG(Phonocardiogram) signals. The main goal of this algorithm is to test it's accuracy in real time applications, such as medical diagnosis and communication systems. The current study leads to different innovations in the field of Adaptive Filtering. One such advancement can be the implementation of adaptive leakage Factor within Recursive Leaky LMS algorithm. The filter can get better stability and better convergence rate by dynamically adapting the Leakage Factor based on the signal characteristics. This will help in combining different signals from different sensors. From the hardware perspective this algorithm can be implemented for designing low power Digital Signal processors using Microcontrollers or FPGAs. Additionally, small AI models can be trained on this algorithm for better outcomes.

3.6 Realistic Constraints:

- Sensitivity to Input Signal Characteristics: Performance of the adaptive filter is highly dependent on the input signal's properties. For instance, PCG signals show vast variability in the noise environment, signal amplitude, and the intrinsic characteristics of the heart sounds themselves. Where the noise is extremely variable or has substantial low-frequency components, the adaptive filter can be faced with challenge in being able to adequately separate the noise from the desired signal effectively. Likewise, the prevalence of strong environmental interference or electronic artifacts can undermine the ability of the filter to converge to the optimal solution. The ability of the filter to adapt to such changing conditions in real-time can be undermined, especially in the case of non-stationary noise, where the noise characteristics vary over time.

- Step size is a very important parameter which requires subtle tuning to achieve optimal performance. Choosing a globally optimal step size for all instances may not be easy. Actual instances of PCG signals are highly variable depending on the patient-specific parameters, the equipment used, and the environmental conditions. Therefore, an optimal step size in one instance may not be optimal in another. Tuning the step size manually may be tedious and infeasible, while automatic tuning mechanisms may add extra complexity or instability.

- Though both the LMS and Leaky LMS are designed to cope with a diverse range of interference types, neither is necessarily ideal when faced with highly structured, periodic forms of interference, such as electrical humming or sustained mechanical noise. In these cases, the method would not be guaranteed to be fully effective in knocking out the exact type of interference unless additional processing is applied alongside. The function of the adaptive filter can equally be undermined should the noise waveform be largely overlap the ranges of the actual PCG signal.

3.7 Engineering Standards:

- IEEE Standard 610.12-1990: (Standard Glossary of Software Engineering Terminology): Software engineering-specific definitions and vocabulary, such as signal processing, are provided by this standard. This is to provide consistent terminology used in describing adaptive filters and signal processing algorithms like LMS and Leaky LMS, and which is in conformity with those used within the field.
- IEEE 2700-2018: (Standard for Digital Signal Processing (DSP) Algorithms): This standard prescribes the requirements for digital signal processing algorithms, including adaptive filtering algorithms. The use of this standard in adhering to certain accuracy and stability requirements by algorithms in medical use ensures that they are satisfactory for use.

3.8 Ethical Bindings:

- Security measures
- Health and safety
- Environmental Responsibility
- Transparency and Accountability
- Privacy protection

3.9 Multidisciplinary Aspects:

The application of a Leaky LMS filter in denoising PCG and speech signals for medical diagnosis is highly multidisciplinary. In clinical medicine and biomedical engineering, denoised PCG signals are critical for precise detection of heart anomalies such as murmurs or valve defects, and denoised speech signals allow for the diagnosis of neurological diseases such as Parkinson's disease or speech impairment. Furthermore, the method brings value to the overall healthcare process with the facilitation of increased accuracy in remote monitoring and telemedicine use. Preventing filter instability and weight explosion, the Leaky LMS filter subsequently is an advantageous method for preserving signal quality with improved diagnostic data and improved patient outcomes.

CHAPTER 4
DESIGN AND METHODOLOGY

4.1 Adaptive Filtering:

The objective of adaptive filtering systems is to eliminate noise without damaging the integrity of the target signal. As a method of limiting the unwanted impacts of noise to the transmission of a voice signal, digital filters like Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) are viable methods of filtration. Advances of the above filters created the platform for the use of adaptive filters. Through a feedback mechanism, the closed-loop adaptive filter enhances its transfer function. These kinds of filters have the potential to be adaptive based on the environment it is exposed to. Parameters that can be adjusted are length, step size, and coefficients. The adaptive algorithm operates in two phases. Filtering comes first, where the input is filtered to output in the standard manner. The second phase, usually referred to as the adaptation weighting stage, involves comparison of the output from the filtering section with the estimated output. The error signal produced is fed back to the controller for updating the weights.

4.2 Noise Cancellation:

The technique of subtracting an associated reference signal from the original signal to reduce or eliminate unwanted interference or noise is known as noise cancellation. It is widely used in numerous applications, including the enhancement of phonocardiogram (PCG) signal by removing background noise and the enhancement of speech signals by eliminating ambient noise. In PCG analysis, noise cancellation helps in the accurate detection of heart sounds by removing artifacts such as lung sounds or muscle noise. Similarly, in speech processing, it improves intelligibility by reducing ambient noise, enabling better communication and more effective automated speech recognition.

4.3 Least Mean Square Algorithm:

One of the popular adaptive filtering techniques applied in machine learning and digital signal processing is the Least Mean Square (LMS) algorithm. Through continually adjusting filter parameters, It successfully reduces the mean square error between the estimated and intended output signals. Rapid processing is facilitated by the LMS algorithm with adaptability demonstrated in adapting to varying conditions and hence enabling optimum performance in uncertain or time-varying input data systems. In automation, learning algorithms, and signal processing, among several applications, the LMS algorithm is still an important and well-held adaptive filtering technique.

Table 4.3 LMS filter calculations

Step	**Equations**	*	**+ or -**	/
	Initialization: w (0) = 0	-	-	-
	For m = 1 to L	-	-	-
1.	$\boldsymbol{Y = W^T X}$	Q	Q – 1	-
2.	$\boldsymbol{E = D - Y}$	-	1	-
3.	**W** (m + 1) = **W**(m) + 2μ**E**(m)**X**(m)	Q + 2	Q	-
	Total	2Q + 2	2Q	-

We used the descending LMS approach to create the following relationships:

$$\nabla_w J[n] = -2p_{dx} + 2Rw(n) \qquad (4.3.1)$$

The elementary choices of the estimators Rx and dx are the immediate estimates defined by

$$R \approx x(n)x^T(n) \quad \text{and} \quad p_{dx} \approx d(n)x(n) \qquad (4.3.2)$$

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

$$w(n+1) = w(n) + 2\mu x(n)[d(n) - w^T(n)x(n)] \qquad (4.3.3)$$

Or,

$$w(n+1) = w(n) + 2\mu e(n)x(n) \qquad (4.3.4)$$

Where

$$y(n) = w^T(n)x(n) \quad \text{(Filter output)} \qquad (4.3.5)$$

And

$$e(n) = d(n) - y(n) \quad \text{(Error)} \tag{4.3.6}$$

The LMS algorithm is made up of the stated algorithms. Every iteration of the method requires knowledge of x(n), d(n), and w(n). If the input signal is a stochastic process, the LMS algorithm provides a stochastic gradient algorithm. As a result, during the iteration, the coefficient vector's pointing direction changes. The LMS filter's equations demonstrate the realization of a FIR adaptive filter.

Where

$$w(n) = [w_0(n), w_1(n), \dots, w_{M-1}(n)]^T \tag{4.3.7}$$

are the filter coefficients and the input data is

$$x(n) = [x(n), x(n-1), .., x(n-M+1)]^T \tag{4.2.8}$$

4.4 Proposed Leaky Least Mean Square (LLMS) Algorithm:

The Leaky Least Mean Squares (Leaky LMS) algorithm is a variation of the Least Mean Squares (LMS) adaptive filtering algorithm, with a minimal "leakage" factor introduced to enhance stability and minimize the likelihood of divergence. The leakage enables the algorithm to have a memory of past values, thus assisting in parameter drift management. The Leaky LMS is used in a broad range of uses, including noise cancellation, system recognition, and adaptive filtering, where performance over a period of time is of highest priority, particularly in applications with varying conditions or noise. It is also extensively applied in speech enhancement and PCG signal processing, where it assists in signal clarity improvement and interference elimination.

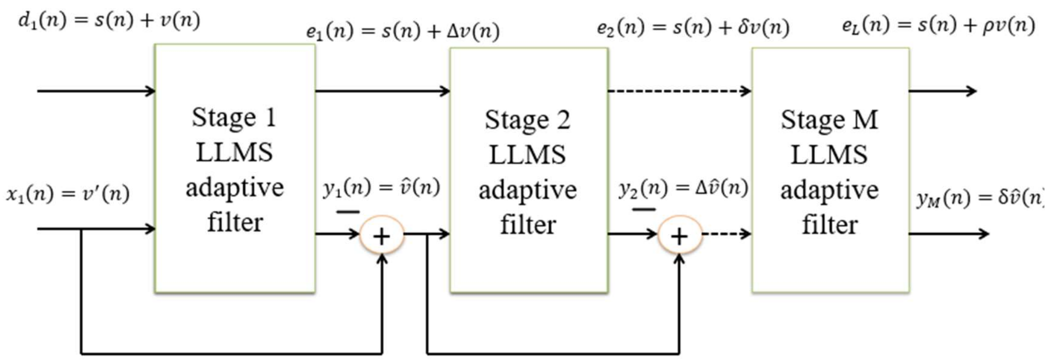

Figure 4.4.1 Block Diagram of Multistage Leaky LMS

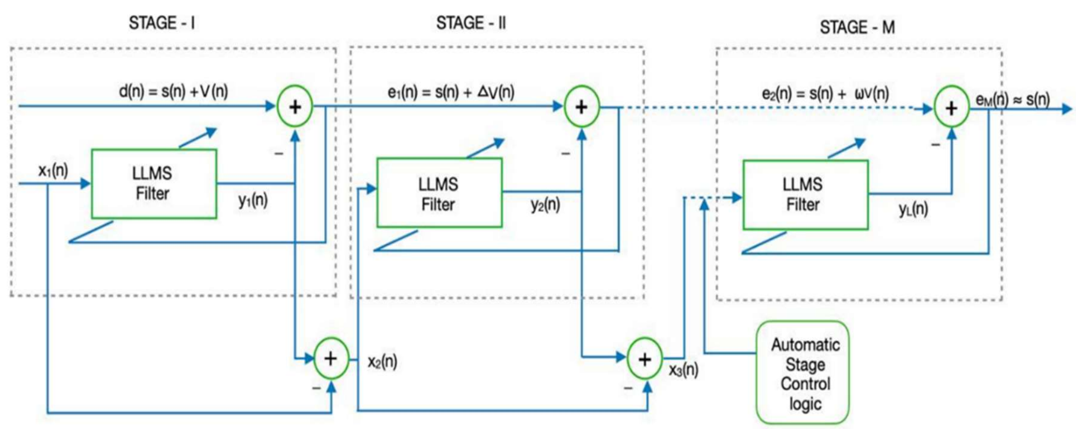

Figure 4.4.2: Proposed Multi-stage Leaky LMS Adaptive Filter

4.4.1 Design Equations

This noise signal, represented by d(m), is the main input signal that is sent to the ANC.

$$d_1(m) = s(m) + v(m) \tag{4.4.1}$$

the signal that the filter receives, $x1(m)$, is linked with the noise signal over the time $p(m)$. The adaptive filter produces a precise replica of the noise signal, as is shown by

$$x_1(m) = v'(m) \tag{4.4.2}$$

In reference to the first step, the outcomes that were achieved by applying the LLMS algorithm are stated as follows:

$$e_1(m) = d_1(m) - y_1(m) \tag{4.4.3}$$

where

$$y_1(m)w(m+1) = (1-\mu\gamma)w(m) + \mu e_1(m)x_1(m) \tag{4.4.4}$$

The weights updating occurs in the following manner:

$$w(m+1) = (1-\mu\gamma)w(m) + \mu e_1(m)x_1(m) \tag{4.4.5}$$

where the added leakage factor is denoted by γ. If either $e1(m)$ or $x1(m)$ is zero then the leakage coefficient is introduced, forcing any undamped modes to zero as well as any existing filter coefficients to zero. μLLMS is the LLMS filter's step-size . Equations (1) and (4) is substituted in (3) to get

$$(1-\mu\gamma)w(m) + \mu[d_1(m) - x_T(m)w(m)]x(m) \tag{4.4.6}$$

$$e_{1LLMS}(m) = s(m) + p(m) - \hat{v}(m) \tag{4.4.7}$$

Likewise, the LMS algorithm determines the following output parameters.

$$y_1(m) = w_1^T(m)x_1(m) = w_1^T(m)v'(m) = \hat{v}(m) \tag{4.4.8}$$

The updated weights are represented by

$$w_1(m+1) = w_1(m) + \mu e_1(m)v'(m) \tag{4.4.9}$$

In the following step, the noise $\Delta v(m)$ is removed from $d2(m)$. The reference input or secondary signal fed to the filter must therefore be a signal that is associated with $\Delta v(m)$. It is given by

$$x_2(m) = x_1(m) - y_1(m) = v'(m) - \hat{v}(m) = \Delta v'(m) \tag{4.4.10}$$

The next stage ANC's inputs are:

$$d_2(m) = e_1(m) = d_1(m) - \hat{v}(m) = s(m) + \Delta v(m) \tag{4.4.11}$$

There is a link between $\Delta v'(m)$ and $\Delta v(m)$. It so turns out to be more successful in reducing noise. As more stages are added, this process is repeated, with the switch for control also playing a part in selecting a suitable algorithm for the next phase. The LLMS's unique feature is its leakage factor, which enhances responsiveness by rapidly reacting to abrupt changes of the provided signal while holding onto some recollection of previous updates. Better stability may be provided by a leaky LMS algorithm, particularly when working with noisy or poorly conditioned PCG signal input signals.

4.4.2 Automatic Stage Control Algorithm

The minimum MSE is achieved exclusively at optimal stage of the filter, as shown in the previous section. To identify this optimal stage, the Pearson cross-correlation function is used, which compares the error signal at each filter stage L, denoted as $e_{\mathrm{L}}(m)$, with the reference noise signal, which is v'(m).

The reference noise is presumed to be v'(m), which is temporally correlated with the additinal noise v(m) , but not correlated with the original, clean signal, s(m). At each stage of the Adaptive Noise Canceller (ANC), the error output $e_{\mathrm{L}}(m)$, serves as An approximation of the clean signal output, i.e $e_L(m)$=$\hat{s}$(m).

As a result, the correlation between v'(m) and $e_L(m)$ decreases when the filter gets closer to its ideal stage. The approximate correlation coefficient between $e_L(m)$ and v'(m) is defined as follows:

$$\rho_{eLm\prime} = \frac{Cov(eL,m\prime)}{\sigma_{eL}\sigma_{m\prime}} \quad (4.4.1.1)$$

In the proposed method, $\rho_{e_{L,},m'}$ denotes Pearson product-moment correlation coefficient, where Cov(e_L,m') represents the covariance between the error signal e_L

and reference noise signal m'. The terms σ_{eL} and $\sigma_{m'}$ indicate the standard deviations of e_L (m) and m' respectively. In this framework, e_L (m) is treated as an approximate of the clean signal at each stage, while v′(m) (also referred to as m′) acts as the reference noise input during the initial stage (Stage I). predicated on the idea that the interest signal, s(m)

is uncorrelated with the added noise, the correlation coefficient $\rho_{e_L,m'}$ is expected to remain low. This correlation function is evaluated at each adaptive filter stage, and additional stages are added iteratively until $\rho_{e_L,m'}$ falls below a predefined threshold, signaling that the optimal filter stage has been reached.

4.5 Recursive Leaky Least Mean Square Algorithm:

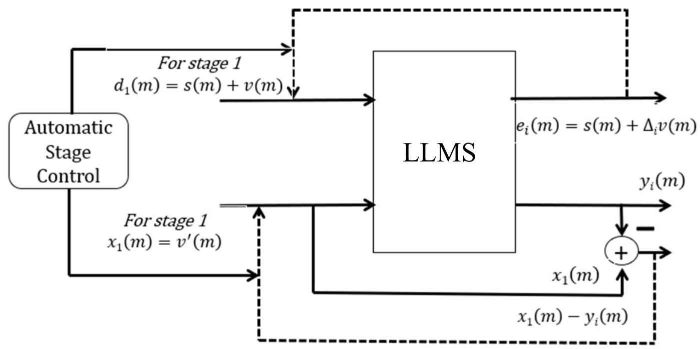

Figure 4.5.1 Block diagram of the Recursive Leaky LMS Adaptive Filter

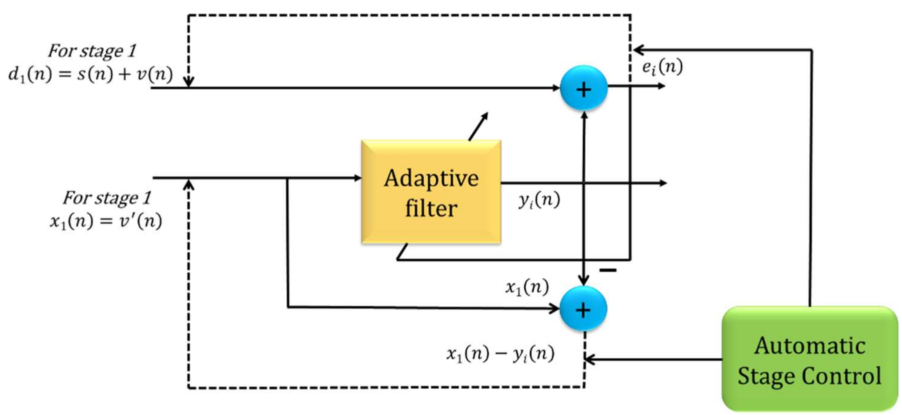

Figure 4.5.2 Schematic diagram of Recursive Leaky LMS Adaptive Filter

Initial conditions**:**

Clean Speech Signal: $s(n)$ (4.5.1)

Noise Signal: $v(n)$ (4.5.2)

Composite Noisy Signal: $d_1(n) = s(n) + v(n)$ (4.5.3)

Reference Noise Signa $x_1(n) = v'(n)$ (4.5.4)

Step-size: μ (4.5.5)

Leakage Coefficient: γ, where $0 < \gamma < 1$ (4.5.6)

Stage 1 – First Stage LLMS Filter

Inputs:

Primary Signal:

$$d_1(n) = s(n) + v(n) \tag{4.5.7}$$

Reference Signal:

$$x_1(n) = v'(n) \tag{4.5.8}$$

Filter Output:

$$y_1(n) = w_1^{\mathrm{T}}(n)\, x_1(n) = \hat{v}(n) \tag{4.5.9}$$

Error Signal:

$$e^1(n) = d^1(n) – y^1(n) = s(n) + v(n) – \hat{v}(n) \quad = s(n) + \Delta v(n) \tag{4.5.10}$$

Weight Update (Leaky LMS):

$$\begin{aligned} w_1(n + 1) &= (1 - \mu\gamma)\, w_1(n) + \mu\, e_1(n)\, x_1(n) \\ &= (1 - \mu\gamma)\, w_1(n) + \mu\, [d_1(n) \;\; x_1^{\mathrm{T}}(n)\, w_1(n)]\, x_1(n) \end{aligned} \tag{4.5.11}$$

Stage 2 – Second Stage LLMS Filter

Inputs:

$$d_2(n) = e^1(n) = s(n) + \Delta v(n) \tag{4.5.12}$$

$$x_2(n) = x_1(n) - y_1(n) = \Delta v'(n) \tag{4.5.13}$$

Output:

$$y_2(n) = w_2^{\mathrm{T}}(n)\, x_2(n) = \Delta\hat{v}(n) \tag{4.5.14}$$

Error Signal:

$$e_2(n) = d_2(n) - y_2(n) = s(n) + \Delta v(n) - \Delta\hat{v}(n) \approx s(n) \tag{4.5.15}$$

Weight Updates:

$$w_2(n + 1) = (1 - \mu\gamma)\, w_2(n) + \mu\, e_2(n)\, x_2(n) \tag{4.5.16}$$

Stage M – Final Stage (Recursive Structure)

Inputs:

$$d_M(n) = e_{M-1}(n) = s(n) + \rho v(n) \tag{4.5.17}$$

$$x(n) = x_1(n) - y_{M-1}(n) = s(n) + \rho v'(n) \tag{4.5.18}$$

Output:

$$y_{\mathrm{m}}(n) = w_{\mathrm{m}}^{\mathrm{T}}(n)\, x_{\mathrm{m}}(n) = \rho\, \hat{v}(n) \tag{4.5.19}$$

Error Signal:

$$e_{\mathrm{m}}(n) = d_{\mathrm{m}}(n) - y_{\mathrm{m}}(n) = s(n) + \rho\, v(n) - \rho\, \hat{v}(n) \approx s(n) \tag{4.5.20}$$

4.5.1 Automatic Stage Control Algorithm

Minimum Mean Squared Error (MSE) is achieved exclusively at optimal stage of the filter, as shown in the previous section. To identify this optimal stage, the Pearson cross-correlation function is used, which compares the distorted signal at each filter stage, denoted as $e_{\mathrm{L}}(m)$, with the reference noise signal as v'(m).

According to the assumption, the referring noise v'(m) is temporally correlated with added noise v(m) , but not correlated with the original, clean signal, which is s(m). At each stage of the Adaptive Noise Canceller (ANC), the error output $e_{\mathrm{L}}(m)$, serves as clean signal's estimation , i.e $e_L(m)$=$\hat{s}$(m).

Therefore, as the filter gets closer to its ideal stage, the correlation between $e_L(m)$ and v'(m) decreases. The estimated correlation coefficient between v'(m) and $e_L(m)$ is defined as follows:

$$\rho_{eLm\prime} = \frac{Cov(eL,m\prime)}{\sigma_{eL}\sigma_{m\prime}} \tag{4.5.1.1}$$

In the proposed method, $\rho_{e_{L},m'}$ denotes the Pearson product-moment correlation coefficient, where Cov(e_L,m') represents the covariance between the error signal e_L and the reference noise m'. The terms σ_{eL} and $\sigma_{m'}$ indicate the standard deviations of e_L (m) and m' respectively. In this framework, e_L (m) is treated as an each stage's assessment of the clean signal, while v′(m) (also referred to as m′) acts as the reference noise input during the initial stage (Stage I). Predicated on the idea that the signalof interests s(m) is uncorrelated with the added noise, the correlation coefficient $\rho_{e_L,m'}$ is expected to remain low. This correlation function is evaluated at each adaptive filter stage, and additional stages are added iteratively until $\rho_{e_L,m'}$ falls below a predefined threshold, signaling that the optimal filter stage has been reached.

4.6 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.

4.7 Design Specifications

4.7.1 Hardware Required

Processor: Intel i5+(2.5 GHz).

Memory: Minimum 4GB RAM

Storage: Required to access MATLAB files.

4.7.2 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.

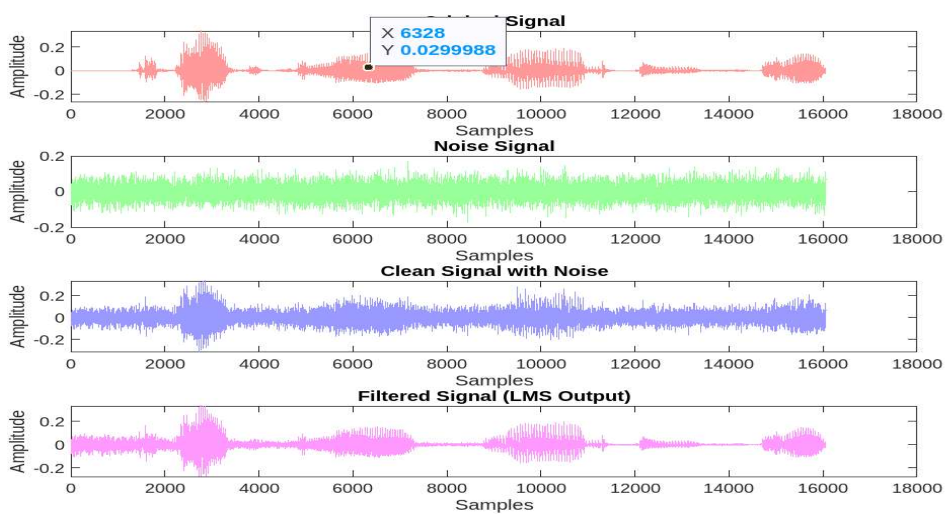

Fig 5.1.1.1: SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1

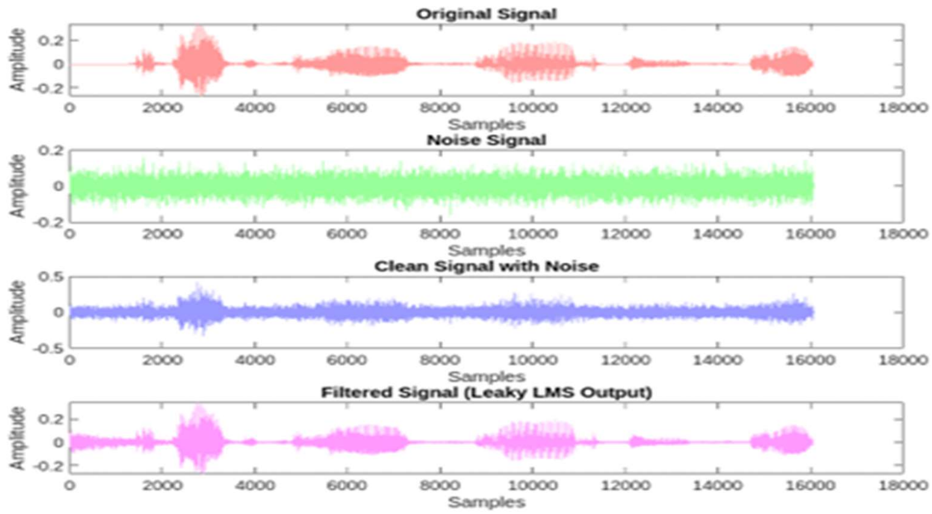

Fig5.1.1.2: SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1

Fig 5.1.1.1 shows the process of noise elimination from the standard speech signal along with added Gaussian noise signal at an input SNR of 0 dB using normal LMS algorithm at stage 1. Whereas Fig 5.1.1.2 represents the noise cancellation from standard speech signal with added Gaussian noise of 0 dB using Leaky LMS algorithm at stage 1. The output from the stage 1 LLMS filter significantly reduces the noise as compared to the normal LMS filter.

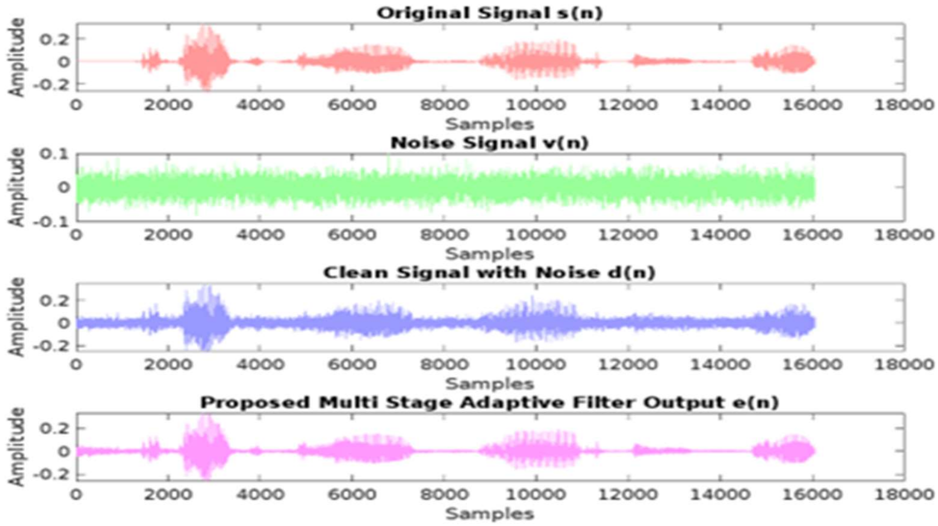

Fig 5.1.2.1: SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 4

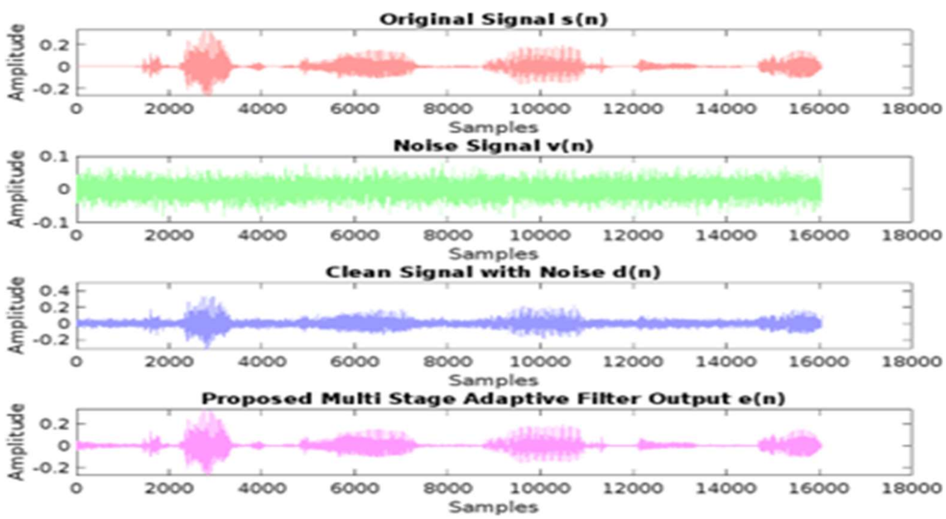

Fig 5.1.2.2: SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 4

Fig 5.1.2.1 shows the process of noise elimination from the standard speech signal along with added Gaussian noise at an input SNR of 0 dB using normal LMS algorithm at stage 4. Whereas Fig 5.1.2.2 represents the noise cancellation from standard speech signal with added Gaussian noise of 0 dB using Leaky LMS algorithm at stage 4. The output from the stage 4 LLMS filter significantly reduces the noise as compared to the normal LMS filter. making the output signal closely match the original clean speech. This shows that the filter does a great job at removing noise without distorting the actual speech signal quality.

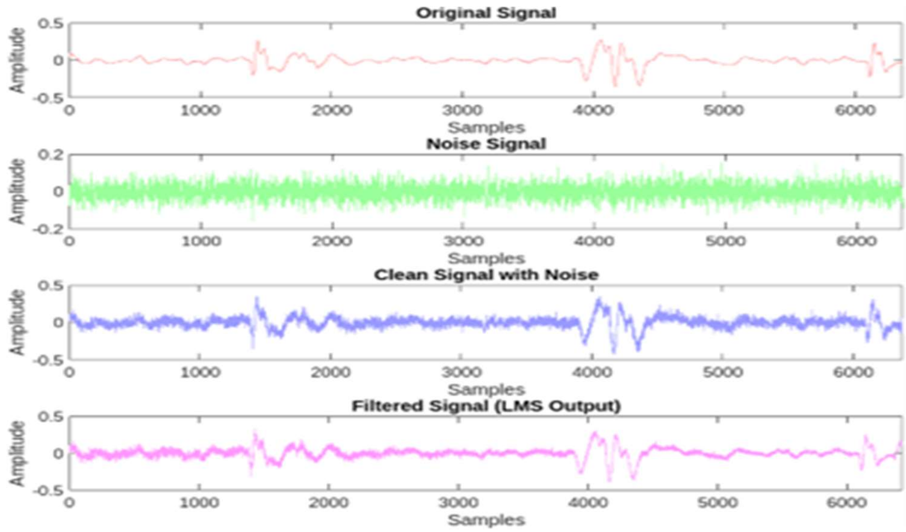

Fig 5.1.3.1: PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1

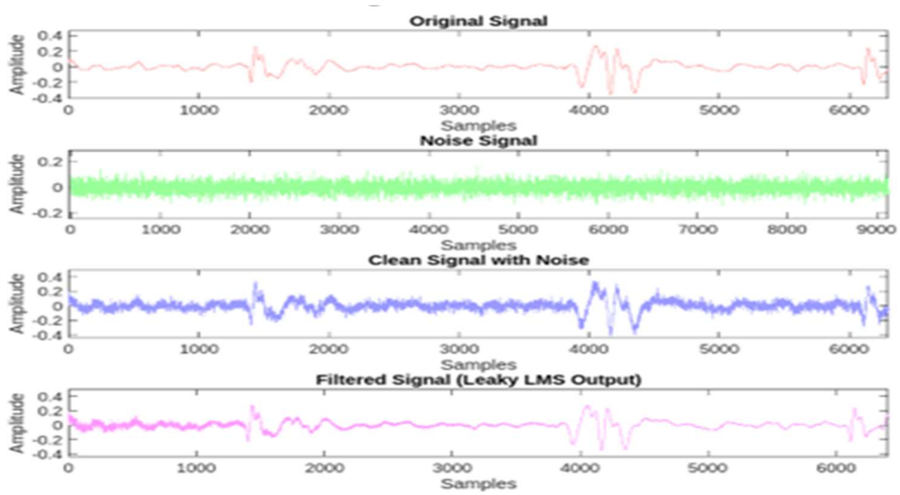

Fig 5.1.3.2: PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1

Fig 5.1.3.1 shows the process of noise elimination from the standard PCG signal with added Gaussian noise at input SNR of 0 dB using normal LMS algorithm at stage 1. Whereas Fig 5.1.3.2 represents the noise cancellation from standard PCG signal with added Gaussian noise of 0 dB using Leaky LMS algorithm at stage 1. The output from the stage 1 LLMS filter significantly reduces the noise as compared to the normal LMS filter.

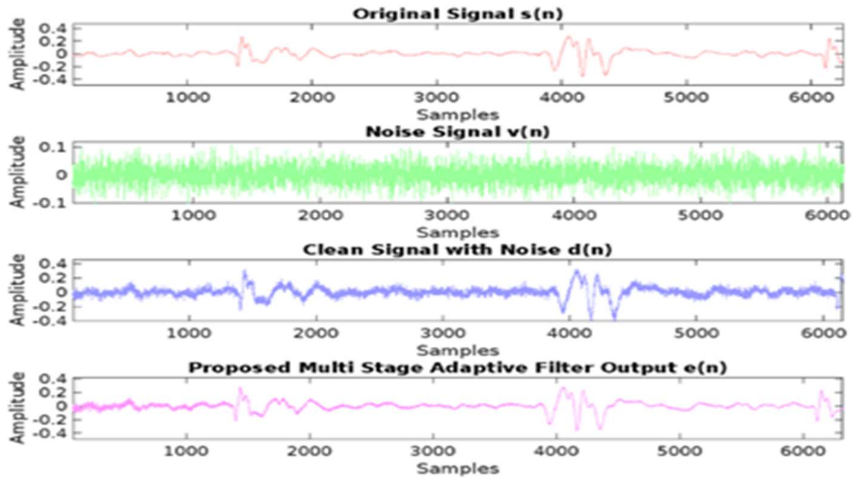

Fig 5.1.4.1: PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 4

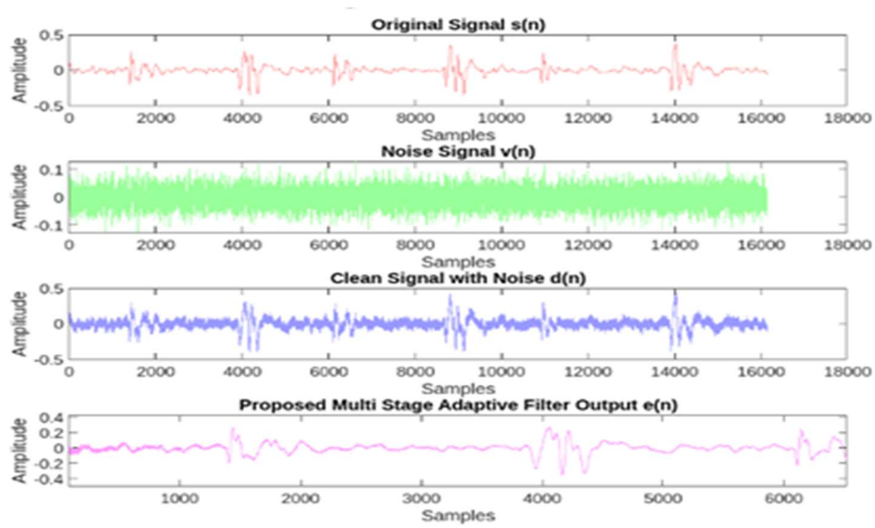

Fig 5.1.4.2: PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 4

Fig 5.1.4.1 shows the process of noise elimination from the standard PCG signal along with added Gaussian noise at an input SNR = 0 dB using normal LMS algorithm at stage 4. Whereas Fig 5.1.4.2 represents the noise cancellation from standard PCG signal with added Gaussian noise of 0 dB using Leaky LMS algorithm at stage 4. The output from the stage 4 LLMS filter significantly reduces the noise as compared to the normal LMS filter.

making the output signal closely match the original clean PCG signal. This shows that the filter does a great job at removing noise without distorting the actual PCG signal quality.

Table 5.1.1: Results for Speech signals with added Gaussian noise using Leaky LMS Adaptive Filter

Input SNR:5dB

STAGE NUMBER	MSE	SNR
Stage 1	0.00010871	20.2909 dB
Stage 2	8.199e-05	21.2149 dB
Stage 3	3.452e-06	27.4779 dB
Stage 4	6.4288e-06	31.3624 dB

Table 5.1.1 illustrates the achievement of the Leaky LMS adaptive filter when applied to speech signals with Gaussian noise at SNR input of 5 dB. This filter demonstrates a consistent increase in output SNR with each stage, with Stage 1 output SNR of 20.2909 dB and Stage 4 achieving a higher SNR of 31.3624 dB. This shows a great improvement in signal clarity. Concurrently, the Mean Square Error (MSE) decreases from 1.08e-4 in Stage 1 to 6.43e-6 in Stage 4, indicating improved noise reduction and greater signal accuracy. These results shows the effective noise cancellation capability of the multistage Leaky LMS filter.

Table 5.1.2: Results for PCG signals with added Gaussian noise using Leaky LMS Adaptive Filter
Input SNR:5dB

STAGE NUMBER	MSE	SNR
Stage 1	0.00011662	17.3809 dB
Stage 2	6.1511e-05	19.553 dB
Stage 3	1.8372e-05	24.3425 dB
Stage 4	7.1978e-06	28.3122 dB

Table 5.1.2 presents the results of applying the Leaky LMS adaptive filter to PCG signals affected by Gaussian noise with SNR input of 5 dB. As signal goes through each stage, it shows clear improvement in signal quality. The SNR increases from 17.3809 dB at Stage 1 to 28.3122 dB at Stage 4, showing that the filter improves the clarity of the signal. At the same time, the MSE decreases from 1.16e-4 in the first stage to 7.19e-6 in the final stage. This steady decrease in MSE indicates that the filter becomes more effective in reducing noise while preserving the original signal quality.

5.2 Conclusion

In this study, we have proposed a multi-stage adaptive filter algorithm using the Leaky LMS (LLMS) algorithm for noise cancellation of speech and Phonocardiogram (PCG) signals. The results have shown that the method effectively removes noise while keeping the original signal intact. By using LLMS in multiple stages, the system adapts to varying noise levels and thus prepares itself for real-world applications where noise is changing.

One of the main benefits of this method is its ability to reduce noise without affecting signal quality to any great degree. Traditional filters have difficulty with this—either removing too much, and thus distorting the signal, or removing too little noise, leaving behind unwanted interference. The multi-stage LLMS process avoids these problems by incrementally building up the signal in a series of stages, eventually producing improved results.

This method is also cost-effective and does not need enormous processing capacity. Unlike sophisticated filtering processes requiring enormous computational power, the multi-stage LLMS method remains efficient and yet offers high-quality output. Therefore, this methodology is applicable in real-time processes such as enhancing speech in phone calls and filtering noise in PCG signals for medical analysis.

The research highlights the capability of adaptive filtering to improve the signal quality in noisy conditions. The improvement in the clarity and noise removal suggests that multi-stage LLMS filtering can be a powerful remedy for practical problems, such as biomedical signal processing and speech communication. Future work can focus on improving the filter parameters for different types of signals and its further application in other signal processing domains.

In conclusion, the study emphasizes the relevancy of adaptive filtering in real-world applications and introduces multi-stage LLMS as an efficient and affordable approach to noise reduction in speech and PCG signals. The results hold promise for future development in signal processing with the guarantee that essential information is preserved and unwanted noise eliminated.

5.3 Future Enhancement

For more effective noise reduction with signal integrity, future research can investigate enhanced recursive multi-stage Leaky LMS (LLMS) filtering algorithms. The system can also realize better convergence and a better capacity to learn from changing noise conditions by simplifying the recursive filtering process. The method's reliability can be improved with the application of advanced parameter optimization methods, e.g., machine learning-based optimization, which can continuously optimize filter coefficients for a range of signal types. Implementing this method in edge computing devices and real-time embedded systems can also enable low-power, high-efficiency noise reduction to be applied to speech processing, technology, and healthcare applications. By ensuring the approach's calculation efficiency and adaptability across a range of real-world environments, these advancements will be accountable for the enhancement of signal clarity.

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