PCG Signal Denoising Using Switched Adaptive Filtering Technique with low-Complexity

18ECP107L- MINOR PROJECT

A PROJECT REPORT

Submitted by

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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 18ECP107L-Minor Project work under 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.

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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.

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TABLE OF CONTENTS

ABBREVIATIONS

LMS-Least Mean Square

LLMS – Leaky Leasy Mean Square

PCG – Phonocardiogram

CHAPTER 1

INTRODUCTION

Phonocardiogram (PCG) signals are critical audio recordings that capture the sounds generated by the mechanical actions within the heart, typically acquired using a stethoscope or advanced microphones designed for medical applications. These signals capture the intricate dynamics of the heart, including the opening and closing of valves and the turbulent movement of blood through the chambers. By capturing these unique sounds, PCG signals provide essential data for medical professionals who analyze them to assess cardiac health, helping to diagnose and monitor conditions such as valve disorders and heart murmurs. Digital signal processing (DSP) techniques allow for detailed analysis by focusing on specific aspects of heart sounds, such as timing intervals, frequency ranges, and amplitude variations. This level of analysis helps clinicians pinpoint and interpret specific cardiac events, aiding in accurate diagnosis and a better understanding of the heart's functionality.

Despite their utility, PCG signals are highly vulnerable to noise contamination from multiple sources, such as environmental sounds, patient movement, electrical interference from devices, and respiratory sounds. This external noise can degrade the signal quality, making it challenging to isolate true cardiac sounds from background interference. In cases where noise significantly distorts the PCG signal, the risk of diagnostic errors increases, potentially leading to misdiagnoses or missed detection of critical conditions. Thus, the removal of such noise is essential to maintain the signal's integrity. Implementing effective noise reduction techniques, including filtering and adaptive noise cancellation, is therefore a critical step to improve the clarity of PCG recordings and make them suitable for accurate cardiac assessment.

Various techniques are available for denoising PCG signals, each designed to address different types of interference. Traditional filters, like low-pass, high-pass, band-pass, and notch filters, work by focusing on specific frequency bands to remove noise based on its frequency content—low-pass filters, for example, can block high-frequency noise from electronics, while notch filters can suppress narrowband interference like power line hum. However, traditional filtering is less effective for complex, varying noise sources. Wavelet transform methods, on the other hand, allow for more advanced noise reduction by analyzing the signal in both time and frequency domains, making it possible to isolate transient noise without losing valuable heart sound data. This method is useful for non-stationary signals like PCG but requires careful tuning and can be computationally demanding. Adaptive filtering, particularly the Least Mean Squares (LMS) algorithm, has become highly preferred for PCG applications due to its real-time adaptability. LMS filtering dynamically adjusts its parameters as it processes the signal, allowing it to adapt to noise patterns that change over time, such as those caused by patient movement or breathing sounds. Unlike static methods, LMS filters "learn" from incoming noise characteristics, making them ideal for dynamic noise environments where traditional methods may fail. LMS filters also balance high efficiency with adaptability, making them well-suited for real-time PCG analysis while preserving key heart sound components. This adaptability ensures that critical cardiac details remain intact, supporting reliable and accurate assessments for clinical use.

In adaptive filtering, LMS filters are widely valued for their simplicity, computational efficiency, and strong adaptability to changing noise conditions, making them ideal for real-time processing of phonocardiogram (PCG) signals. In cardiac monitoring, LMS-based adaptive filtering significantly enhances the clarity of heart sounds by accurately distinguishing them from unpredictable noise sources—such as respiratory sounds, body movements, and other external interferences—that could otherwise obscure crucial cardiac information. This improved signal quality is essential for enabling healthcare providers to make precise, reliable interpretations, minimizing the risk of diagnostic errors and ultimately contributing to enhanced patient outcomes.

Furthermore, the Leaky LMS filter, a refined version of the standard LMS algorithm, offers additional advantages by addressing the issue of weight drift, a challenge that can arise in prolonged applications of LMS filtering. Through the introduction of a "leakage" factor, the Leaky LMS filter helps prevent filter coefficients from growing uncontrollably, thereby improving stability and reliability in dynamic noise environments where signal conditions frequently fluctuate. This built-in “leakage” adjustment ensures more consistent performance and better handling of diverse noise sources over extended periods.

By integrating both LMS and Leaky LMS filters in PCG signal processing, it is possible to leverage the strengths of each: while the standard LMS filter efficiently adapts to basic noise variations, the Leaky LMS filter adds an extra layer of robustness, enhancing stability and ensuring that critical heart sounds remain clear and discernible across extended monitoring sessions. Together, these filters provide a comprehensive approach to adaptive noise cancellation, maintaining the integrity and usability of PCG recordings in clinical settings, thus supporting accurate and reliable cardiac assessments.

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.
Published in 2022 in the International Journal of Electronics and Communications.	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.
published in 2022 in the *Journal of Healthcare Engineering*.	A Low-Cost Multistage Cascaded Adaptive Filter Configuration for Noise Reduction in Phonocardiogram Signal	This study introduces a cost-effective multistage cascaded adaptive filter using the Sign Error LMS (SELMS) algorithm for efficient PCG signal denoising. The filter demonstrates improved noise reduction, achieving better signal-to-noise ratio (SNR) and mean square error (MSE) performance, enhancing PCG signal clarity in noisy conditions.

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

Phonocardiogram (PCG) signals, which record the acoustic emissions of the heart, are essential for diagnosing cardiovascular conditions by providing detailed insights into the heart's functioning and valve activity. However, these signals are often contaminated by various sources of noise, including environmental sounds, electronic interference, and artifacts resulting from patient movement. This noise significantly impairs the quality of the signal, making accurate interpretation difficult and challenging for clinicians. Despite the critical need for effective noise reduction, current denoising methods, such as Empirical Mode Decomposition (EMD), Wavelet Transforms, and Deep Learning-based techniques, are often too complex and computationally demanding, limiting their feasibility for real-time applications or use in environments where computational resources are constrained. Additionally, these methods may not always provide the desired trade-off between performance and resource efficiency, especially when deployed in resource-limited or time-sensitive settings.

One potential solution to this challenge is adaptive filtering, particularly the Least Mean Squares (LMS) algorithm, which has gained popularity due to its simplicity and ease of implementation. The LMS algorithm works by iteratively adjusting the filter weights to minimize the error between the filtered output and a reference signal. However, while LMS offers a straightforward and computationally efficient solution, it faces several limitations. These include slower convergence rates, reduced accuracy in complex environments, and potential instability when dealing with signals that require high precision in noise reduction, such as those encountered in PCG signal processing. As a result, LMS-based filters are often less effective in delivering the high-quality, real-time noise reduction needed for clear heart sound analysis.

To overcome these challenges, our project proposes the application of the Leaky LMS algorithm, a modification of the traditional LMS that introduces a "leakage" factor. This leakage factor helps to control the growth of filter weights, preventing them from becoming excessively large and causing instability. By doing so, Leaky LMS improves the stability of the adaptive filter and allows for faster convergence, making it more effective in handling the varying and often unpredictable noise sources that affect PCG signals. This enhanced adaptability is critical for real-time applications, where the filter must continuously adjust to dynamic conditions.

The innovation of this project lies in the development of a two-stage adaptive filtering system that integrates both the LMS and Leaky LMS algorithms. In this dual-stage approach, the LMS algorithm serves as the first stage, performing an initial noise reduction by minimizing error through its simple iterative process. The Leaky LMS algorithm is then applied in the second stage to refine the signal further, enhancing noise reduction while maintaining stability and improving convergence speed. By leveraging the strengths of both algorithms, this two-stage switched filter aims to provide a more accurate, adaptive, and computationally efficient solution for PCG signal denoising.

The unique contribution of this research is the first-time application of the Leaky LMS algorithm to PCG signal denoising, offering a practical and efficient alternative to more complex methods. This dual-stage adaptive filtering approach holds significant promise for improving the quality of PCG signals in real-time applications, particularly in clinical and resource-limited environments. By providing a balance between performance and efficiency, this project seeks to make PCG signal processing more accessible and reliable, ultimately contributing to more accurate cardiovascular diagnostics and better patient care.

3.2 Scope for the study

The scope of this study focuses on advancing PCG signal processing by developing a novel two-stage switched adaptive filter that integrates both the LMS and Leaky LMS algorithms. This research aims to address the limitations of traditional LMS filtering in handling the complex noise patterns commonly associated with PCG signals, which can include environmental noise, electronic interference, and other unpredictable sources.

By designing a two-stage filtering system, this study explores the potential of using LMS for initial noise suppression, followed by Leaky LMS to further refine the signal. The study will examine the adaptive properties of the Leaky LMS algorithm, particularly its effectiveness in maintaining stability under variable noise conditions and its ability to achieve faster convergence without sacrificing accuracy. The proposed system is expected to offer an efficient, low-complexity solution suitable for real-time applications, including clinical environments and resource-constrained settings.

Through simulations and experimental evaluations, this research seeks to assess the performance of the two-stage filter in terms of noise reduction, signal quality preservation, and computational efficiency. By providing a simpler alternative to more complex denoising methods, this study has the potential to contribute to more accessible and accurate PCG signal analysis, ultimately supporting improved cardiovascular diagnostics and patient care.

3.3 Objective of the study

The primary objective of this research is to design and implement an adaptive filter system that effectively mitigates noise in phonocardiogram (PCG) signals, enhancing the clarity and accuracy of heart sound recordings. The goal is to significantly improve the signal-to-noise ratio (SNR) while minimizing estimation errors during the denoising process, ensuring that the processed PCG signals retain their diagnostic value. The solution must be based on an algorithm that strikes a balance between simplicity and performance, providing an efficient, real-time filtering solution that can be readily applied in practical scenarios. Given the potential challenges posed by real-time processing requirements and limited computational resources in many clinical settings, the proposed method aims to offer a straightforward yet effective approach to noise cancellation without sacrificing accuracy or processing speed. The adaptive filtering system should be capable of responding dynamically to the varying and unpredictable nature of noise in PCG signals, ensuring that it can perform consistently under different conditions.

To address this challenge, we propose a two-stage feed-forward switched adaptive filter model tailored for active noise control (ANC) systems. This model incorporates both the traditional Least Mean Squares (LMS) algorithm and the Leaky LMS algorithm in a sequential manner. The first stage of the filter uses LMS to perform initial noise reduction through its straightforward error-minimizing process. The second stage employs Leaky LMS, which incorporates a leakage factor to enhance stability and improve the convergence rate. This two-stage system dynamically adapts to the noise characteristics, ensuring efficient filtering while preserving the integrity of the PCG signal for accurate cardiovascular diagnostics.

The innovative aspect of this approach lies in the dynamic switching between two signed versions of the LMS algorithm within each filter stage. By alternating between the LMS and Leaky LMS algorithms, the system optimizes the denoising process at each stage based on the changing characteristics of the noise and signal. This switching mechanism allows the filter to leverage the strengths of both algorithms—LMS for its simplicity and direct adaptation, and Leaky LMS for its enhanced stability and faster convergence. This adaptive switching between algorithms ensures that the system can deliver superior results, with minimal noise interference and improved accuracy in heart sound detection. Through this innovation, the model provides an effective, low-complexity solution that meets the demands of real-time PCG signal processing while maintaining high-quality performance.

3.4 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.

3.4 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.

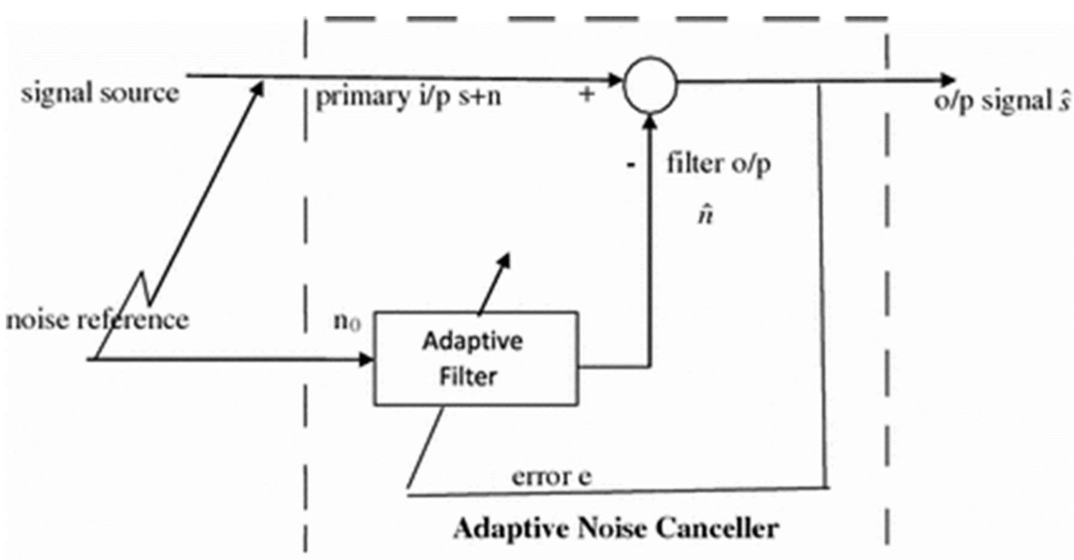

Figure 4. 1

(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 signal in order to reduce or eliminate undesirable noise or interference is known as noise cancellation. It is frequently utilised for a number of purposes, such as reducing the amount of noise in foetal ECG data by suppressing the maternal ECG component.

(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:

Due to its ability to manage parameter drift, the leaky LMS algorithm has been the subject of much research. The inadequate excitation in the input sequence is connected to this surprising characteristic drift. Additionally, leaky LMS algorithms often employ limited step sizes to require a trade off between tiny constant state distortion and quick rapid convergence. This study proposes the variable step-size (VSS) leaky LMS method. Additionally, the time average estimating of the normalised amount and the time average estimation of the error are combined in the measurement step-size technique. The suggested variable step-size approach, when combined with the leaky LMS algorithm, can successfully remove disturbances from noise, achieve early convergence, and produce final minor misalignments. Simulation findings show that the suggested algorithm performs better compared to others

(VI) Signed Error (SE)LMS:

The Sign Error A variant of the Least Mean Square (LMS) algorithm, the SE-LMS technique is intended for adaptive filtering and noise-cancelling purposes where reliability and computing economy are crucial. By adjusting filter coefficients based solely on the error signal's sign rather than the signal itself, the SE-LMS algorithm alters the conventional LMS methodology. Because of this, SE-LMS is especially helpful when obtaining precise values for errors is challenging or when computational resources are scarce. The precise error across the intended output and the filter output is used to update the filter weights in the conventional LMS method. To modify the filter coefficients in a way that minimises the mean square error, this error is multiplied by the input signal.

(VII) SD-LMS:

The Signed Information An version of the Least Mean Square (LMS) method, the Least Mean Square (SD-LMS) algorithm is intended for effective adaptive filtering with reduced processing demands. Instead than depending on the entire magnitude of the data, SD-LMS updates the filter's weights based solely on the direction or "sign" of the incoming data. Because of this simplification, fewer multiplications are required, which is especially helpful in real-time applications where speed is crucial or in systems with constrained processing capability.Because the simplification may result in a less accurate adaptation, SD-LMS works best in applications that can withstand a little slower convergence and less precision. In spite of this trade-off, SD-LMS is nevertheless useful because of its efficiency and resilience in settings with limited computational resources.

(VIII) Switching:

Switching is the process of choosing the top-performing filter from a group of potential filters according to a predetermined standard, such minimum error. The system "switches" to a different filter that is more appropriate for the new circumstances when the signal environment changes. This method offers flexibility and guarantees the best possible filter performance, making it especially helpful in dynamic settings with fluctuating signal characteristics.

(IX) Cascading:

By connecting many filters in series, cascading allows the output of one filter to feed into the next. With this configuration, each filter can target a distinct feature of the signal or noise, gradually improving the output. Cascading enhances accuracy through layered processing, making it useful in complex situations when a single filter cannot provide the required performance.

(4.1.2) Methodology:

(I) The LMS Algorithm Methodology:

we developed the following relations using the descent LMS method:

$$\nabla_w J[n] = -2p_{dx} + 2Rw(n) \qquad (1)$$

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

$$R \approx x(n)x^T(n) \quad \text{and} \quad p_{dx} \approx d(n)x(n) \qquad (2)$$

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

$$w(n+1) = w(n) + 2\mu x(n)[d(n) - w^T(n)x(n)] \qquad (3)$$

Or,

$$w(n+1) = w(n) + 2\mu e(n)x(n) \qquad (4)$$

Where

$$y(n) = w^T(n)x(n) \quad \text{(Filter output)} \qquad (5)$$

And

$$e(n) = d(n) - y(n) \quad \text{(Error)} \qquad (6)$$

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

$$w(n) = [w_0(n), w_1(n), \dots, w_{M-1}(n)]^T \qquad (7)$$

Are the filter coefficients and the input data is

$$x(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T \qquad (8)$$

(II) Leaky LMS Algorithm:

Initial conditions**:**

Input Signal: $\{\ x(n)\ \}$

Desired signal: $\{\ d(n)\ \}$

Filter Coefficients: $\{\ w(n)\ \}$

Step-size: μ

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

Autocorrelation matrix: R_x

Mean Convergence Condition:

The LMS algorithm ensures that

$$\lim_{n\to\infty} E\,\{w(n)\} = R_x^{-1}p \qquad (1)$$

Equation after the weight update:

$$E\{w(n+1)\} = E\{w(n)\} + \mu E\{d(n)x(n)\} - \mu E\{x(n)x(n)^T w(n)\} \qquad (2)$$

Updated LMS Equation:

$$E\{w(n+1)\} = (I - \mu R_x)E\{w(n)\} + \mu p \qquad (3)$$

For Stable convergence of LMS:

$$0 < \mu < \frac{2}{\lambda_{\max}}$$

Where $\lambda_{\max}$ is the largest eigenvalue of Rx.

The LMS algorithm with leakage modifies the update as:

$$w(n+1) = (1 - \mu\gamma)w(n) + \mu[d(n) - x(n)^T w(n)]x(n) \qquad (4)$$

The effect of leakage:

$$\lim_{n\to\infty} E\,\{w(n)\} = (R_x + \gamma I)^{-1}p \qquad (5)$$

The Proposed Switched Adaptive Methodology:

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

$$d_1(m) = s(m) + p(m) \qquad (1)$$

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

$$x_1(m) = p'(m) \qquad (2)$$

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

$$e_1(m) = d_1(m) - y_1(m) \qquad (3)$$

where

$$y_1(m)w(m+1) = (1 - \mu\gamma)w(m) + \mu e_1(m)x_1(m) \qquad (4)$$

The updating of weights occurs in the following manner:

$$w(m+1) = (1 - \mu\gamma)w(m) + \mu e_1(m)x_1(m) \qquad (5)$$

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

$$(1 - \mu\gamma)w(m) + \mu[d_1(m) - x_T(m)w(m)]x(m) \qquad (6)$$

$$\& \qquad e_{1LLMS}(m) = s(m) + p(m) - \hat{p}(m) \qquad (7)$$

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

$$y_1(m) = w_1^T(m)x_1(m) = w_1^T(m)p'(m) = \hat{p}(m) \qquad (8)$$

The updated weights are given by

$$w_1(m+1) = w_1(m) + \mu e_1(m)p'(m) \qquad (9)$$

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:

$$x_2(m) = x_1(m) - y_1(m) = p'(m) - \hat{p}(m) = \Delta p'(m) \qquad (10)$$

The subsequent stage ANC's inputs are:

$$d_2(m) = e_1(m) = d_1(m) - \hat{p}(m) = s(m) + \Delta p(m) \qquad (11)$$

$\Delta p'(m)$ 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 speciality 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:

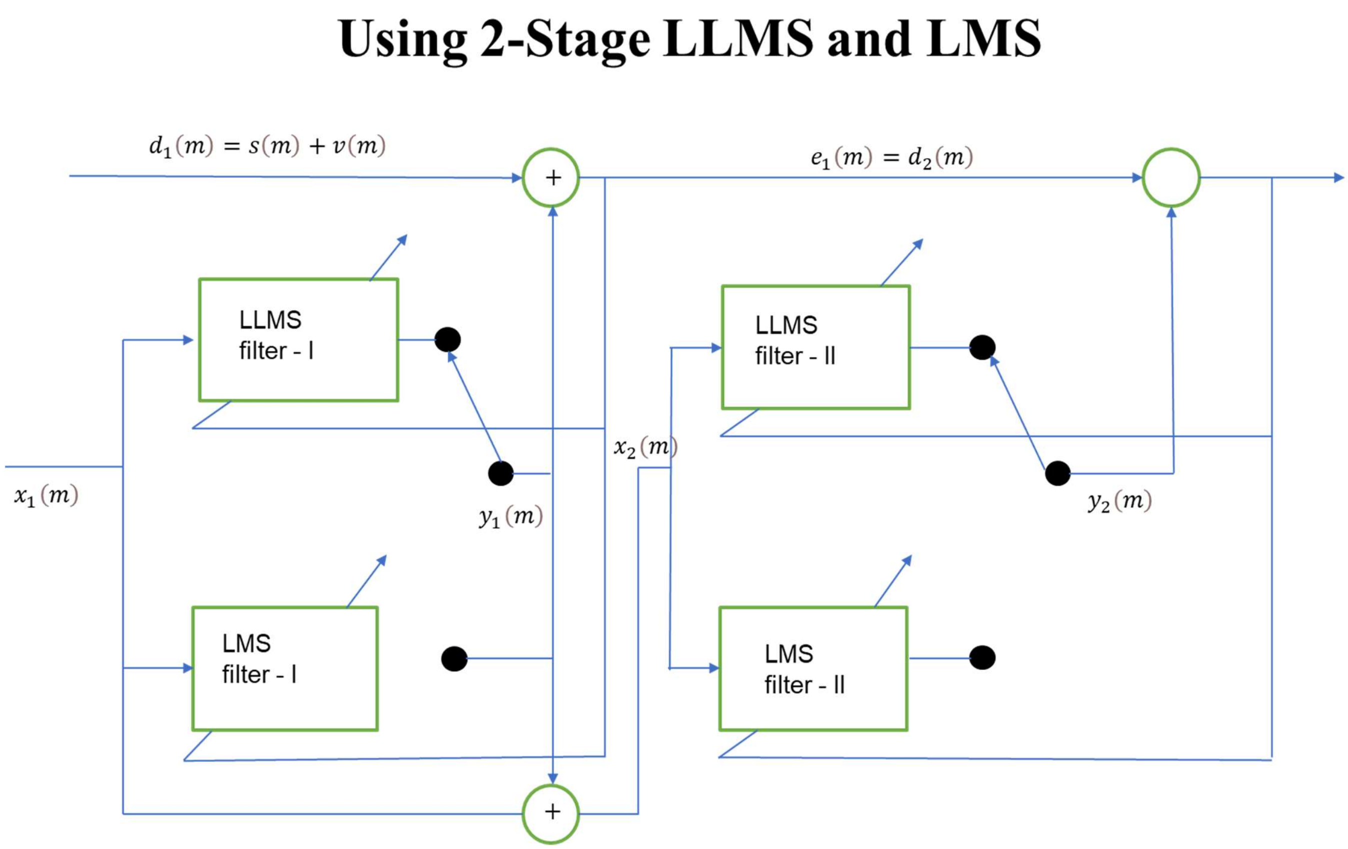

Figure 4. 2

Figure 4.1 illustrates a two-stage adaptive filtering architecture utilizing both Least Mean Squares (LMS) and Logarithmic LMS (LLMS) algorithms. In this setup, the input signal x1 passes through two adaptive filters (LLMS filter - I and LMS filter - I), producing intermediate output y1. This output is further processed in the second stage by LLMS filter - II and LMS filter - II to generate the final output y2 and the error signal e1. This multi-stage approach leverages both LMS and LLMS filters to enhance noise reduction and signal clarity by minimizing error between desired signal d1 and the output.

(V) Switching Algorithm for 2-Stage LLMS and LMS Filters

1. Initialize: Define a threshold T to determine when to switch filters based on performance.
2. Stage 1:
    a. Pass the input signal through both the LLMS and LMS filters in parallel.
    b. Measure the performance (e.g., error or MSE) of each filter

c. Choose the filter with the better performance. If the LLMS filter has lower error and meets the threshold T, use its output; otherwise, use the LMS filter's output for the next stage.

3. Stage 2:
   a. Feed the selected output from Stage 1 into both the LLMS and LMS filters for Stage 2.
   b. Again, evaluate each filter's performance and choose the output with the best result, favoring the LLMS filter if it meets the performance threshold.
4. Adapt and Repeat: Update the filter parameters based on the observed errors, then apply the process to the next signal sample.

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)

4.3.3 Dataset Requirement

For this study, we utilized the "PhysioNet/CinC Challenge 2016: Training Sets," focusing specifically on heart wave recordings a0001 and a0007 at 2kHz sampling rates to compare normal and abnormal waveforms. Gaussian distributions were generated using MATLAB, with pink noise from Audacity serving as reference noise for analysis.

CHAPTER 5

Results and Discussion:

5.1 Experimental Results:

The proposed filter's ability to reduce noise in PCG signals contaminated by external interference has been thoroughly assessed. Figure 1 highlights the denoising performance of the LLMS-LMS switched filter, demon strating its effectiveness in recovering a clean signal from a noise-corrupted one. The findings indicate that the filter's output closely matches the clean signal without noise, confirming its effectiveness in mitigating external noise in PCG signals. The two-stage LLMS-LMS automatic switched filter proves capable of distinguishing and eliminating unwanted noise, ultimately restoring the PCG signal.

Tabulation Format:

Input	Filter Structure	MSE	SNR(dB)
	1-S SELMS AF	2.05E-04	31.7715
Gaussian	1-S SDLMS AF	2.14E-04	30.0184
+2dB	2-S Feedforward filter	1.33E-04	35.7694
	Proposed 2-stage LMS Switched AF	8.33E-05	39.8008
	1-S SELMS AF	1.96E-04	31.6973
Pink	1-S SDLMS AF	1.92E-04	31.9029
-2dB	2-S Feedforward filter	2.10E-04	31.0102
	Proposed 2-stage LMS Switched AF	6.48E-05	42.7826

Table 5.1: MSE and SNR for different AF Structures for Normal PCG

Input	Filter Architecture	MSE	SNR (db)
Gaussian +2 dB	1-S SELMS AF	2.05E-04	31.7715
	1-S SDLMS AF	2.14E-04	30.0184
	2-S feedforward filter	1.33E-04	35.7694
	Existing 3-S feedforward filter	1.11E-04	33.8388
	Existing V-S feedforward filter	1.02E-04	34.8574
	Proposed 2-stage LMS Switched AF	**8.33E-05**	**39.8008**
Pink -2 dB	1-S SELMS AF	1.96E-04	31.6973
	1-S SDLMS AF	1.92E-04	31.9029
	2-S feedforward filter	2.10E-04	31.0102
	Existing 3-S feedforward filter	1.18E-04	36.817
	Existing V-S feedforward filter	9.50E-05	38.9575
	Proposed 2-stage LMS Switched AF	**6.48E-05**	**42.7826**

Table 5.2: MSE and SNR for different AF Structures for Pathological PCG

Waveform Representation of Results:

(I)LMS Output:

The first waveform shows the Clean PCG Signal , the second waveform shows the PCG signal along with the added noise and the third waveform represents the Denoised signal using LMS Algorithm.

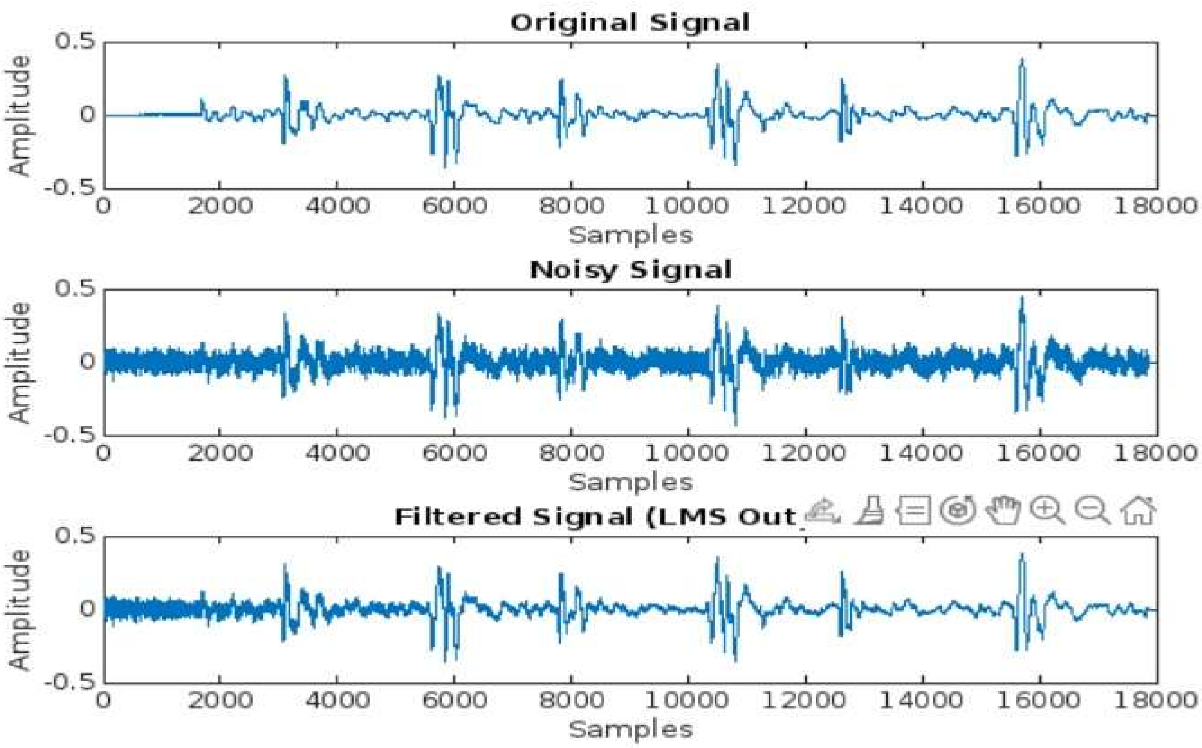

Figure 5. 1

(II) Leaky LMS Output:

Similarly ,the first waveform shows the Clean PCG Signal , the second waveform shows the PCG signal along with the added noise and the third waveform represents the Denoised signal using Leaky-LMS Algorithm.

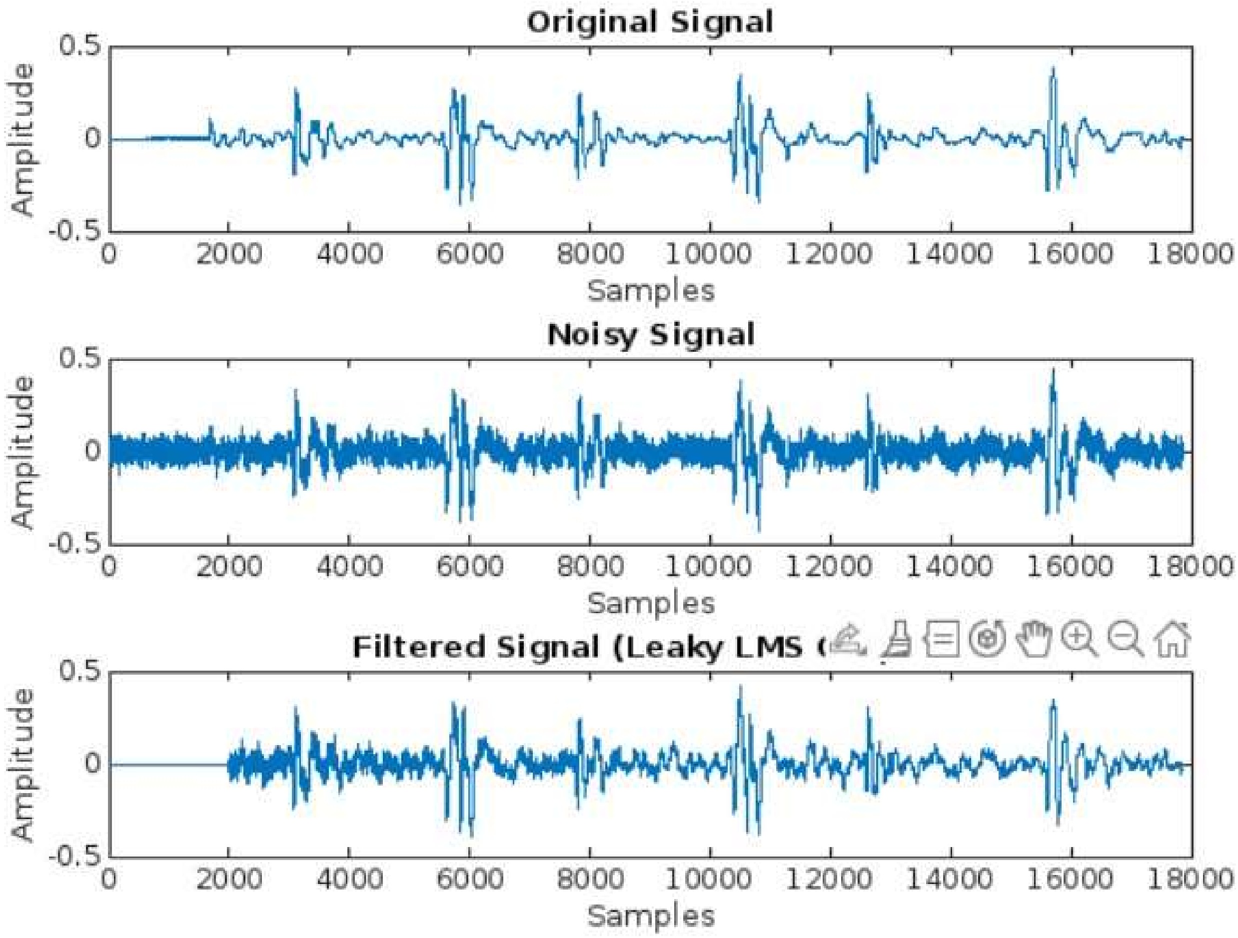

Figure 5. 2

5.2 Accuracy:

By Comparing the SNR and MSE Values from the Table 1 (For Normal PCG) and from the Table 2 which is for Pathological PCG , we can conclude that the proposed 2 stage switched adaptive filtering technique is more accurate than SELMS , SDLMS and other feed forward adaptive filtering techniques.

5.3 Suggestion and Recommendations:

It is recommended that the user, who is not very familiar with MATLAB, review this appendix and attempt to use the material before beginning to use the project.

Creating a directory specifically for a project and storing our own MATLAB m-files within it makes things less confused.

Nevertheless, the directory needs to be included in the MATLAB path if we use any of these files.

5.4 Conclusion:

This work introduces a switched adaptive filter model based on LLMS and LMS algorithms as a reliable technique for signal denoising. Because of its versatility, the LMS filter is especially helpful in settings with erratic and changing noise patterns. Simulation results show that this filter performs better than existing adaptive filter architectures and offers a more cost-effective way to reduce noise.

5.5 Future Enhancement:

For future enhancement the same algorithm can be implemented on different types of signals like ECG ,EEG and other various normal and pathological signals .

Similarly different adsptive filtering can be used on the same signals to get better output for future purpose which can be simpler as well as cost-effective along with the novelty of the work.

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APPENDIX