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

Kunal keshan,Sahil Sharma,Swapnil Maiti,Deekshitha Adusumalli,S. Hannah Pauline
Department of Electronics and Communication Engg., College of Engineering and Technology
SRM Institute of Science and Tech.,SRM Nagar,
Kattankulathur, Kanchipuram,Chennai, India

***Abstract*—Phonocardiography, a non-invasive diagnostic technique, involves the recording of heart sounds using a microphone placed on the chest. The resulting phonocardiogram (PCG) signal provides valuable insights into the mechanical function of the heart, enabling the detection of various cardiac abnormalities. Noise in phonocardiogram (PCG) signals can significantly degrade their quality and hinder accurate diagnosis. Common sources of noise include electrical interference, muscle artifacts, respiratory sounds, environmental noise, baseline wander, and microphone noise. These factors can introduce artifacts that resemble heart sounds, making it difficult to distinguish between normal and abnormal cardiac activity. To mitigate the impact of noise, researchers often employ signal processing techniques such as filtering, noise reduction, and artifact removal.**

***Index Terms*—Least Mean Square, Cancellation of adaptive Noise, SELMS, SDLMS**

I. Introduction

Phonocardiography, a non-invasive diagnostic tool, utilizes a microphone placed on the chest to capture the mechanical sounds produced by the heart. These sounds, known as heart murmurs or clicks, provide valuable information about the heart's structure, function, and the presence of abnormalities. However, the quality of phonocardiogram (PCG) signals can be compromised by various noise sources, including electrical interference, muscle movements, respiratory sounds, environmental noise, and microphone imperfections. These extraneous sounds can mask or mimic genuine cardiac signals, leading to misinterpretation and inaccurate diagnosis. To address these challenges, researchers have developed signal processing techniques that can effectively isolate and remove noise from PCG recordings, enhancing the reliability and diagnostic accuracy of this valuable diagnostic tool. LMS (Least Mean Squares) filters are a powerful tool for denoising PCG (Phonocardiogram) signals. These adaptive filters work by iteratively adjusting their coefficients to minimize the error between the filtered signal and a desired signal. In the context of PCG denoising, the desired signal is typically the clean, noise-free version of the PCG. By analyzing the statistical characteristics of the noise and the PCG signal, the LMS filter can effectively remove the noise while preserving the important features of the underlying cardiac sounds. This is particularly useful in clinical applications where accurate analysis of PCG signals is crucial for diagnosing heart conditions. In this paper denoising the PCG signal is implemented using Swtiched least mean square filter and Leaky Least mean square filters to achieve the result.

II. PROPOSED FEED-FORWARD SWITCHED FILTER

The signal with noise, denoted as $d(m)$ constitutes the primary input signal directed to the ANC. $d_1(m) = s(m) + p(m)$, In the given scenario, $s(m)$ represents the signal without noise, while $p(m)$ represents the introduced noise. It is essential to emphasize that $s(m)$ and $p(m)$ are uncorrelated in time. However, the signal supplied to the filter, $x_1(m)$, 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

$$d_1(m) = s(m) + p(m). \tag{1}$$

$$x_1(m) = p^{'}(m). \tag{2}$$

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

$$e_1(m) = d_1(m) - y_1(m) \tag{3}$$

where

$$\begin{aligned} y_1(m) &= \mathbf{w}_1^T(m)\mathbf{x}_1(m) \\ &= \mathbf{w}_1^T(m)\mathbf{p}^{'}(m) \\ &= \hat{p}(m), \end{aligned} \tag{4}$$

where $\mathbf{w}(m) = [w_0, w_1, ...w_K]^T$ displays the filter's weights and $\mathbf{x}_i(m) = [x_1(m), x_2(m-1), ...x_m(m-K+1)]^T$ denotes its input, where K is the filter order.

The updating of weights occurs in the following manner:

$$w(m+1) = (1-\mu\gamma)w(m) + e_1(m)x_1(m) \tag{5}$$

$$= (1-\mu\gamma)w(m) + [d_1(m) - x_T(m)w(m)]x(m) \tag{6}$$

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 $e_1(m)$ or $x_1(m)$ is zero. μ_{LLMS} is the step-size of LLMS filter.
Equations (1) and (4) can be substituted in (3) to obtain

$$\begin{aligned} e_{1LLMS}(m) &= s(m) + p(m) - \hat{p}(m) \\ &= s(m) + \Delta_1 p(m) \end{aligned} \tag{7}$$

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

$$\begin{aligned} y_1(m) &= \mathbf{w}_1^T(m)\mathbf{x}_1(m) \\ &= \mathbf{w}_1^T(m)\mathbf{p}^{'}(m) = \hat{p}(m), \end{aligned} \tag{8}$$

The updated weights are given by

$$\mathbf{w}_1(m+1) = \mathbf{w}_1(m) + \mu e_1(m)\mathbf{p}^{'}(m), \tag{9}$$

μ is the step-size of LMS filter.

$$\begin{aligned} e_{1LMS}(m) &= s(m) + p(m) - \hat{p}(m) \\ &= s(m) + \Delta_2 p(m) \end{aligned} \tag{10}$$

We notice that Equations (7) and (10) both yield an estimation of $s(m)$, but they employ the LLMS and LMS algorithms, respectively. The control switch discerns the algorithm that produces the most precise estimation of $s(m)$ from the two, and the outputs associated with this choice are utilized in the second stage. Following the selection of the best algorithm, the first-stage outputs are as follows:

$$y_1(m) = \hat{p}(m) \tag{11}$$

and

$$\begin{aligned} e_1(m) &= d_1(m) - y_1(m) \\ &= s(m) + p(m) - \hat{p}(m) = s(m) + \Delta p(m) \end{aligned} \tag{12}$$

The subsequent stage ANC's inputs are:

$$\begin{aligned} d_2(m) &= e_1(m) = d_1(m) - \hat{p}(m) \\ &= s(m) + \Delta p(m) \end{aligned} \tag{13}$$

The next stage aims to eliminate the noise $\Delta p(m)$ from $d_2(m)$.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:

$$\begin{aligned} x_2(m) &= x_1(m) - y_1(m) = p^{'}(m) - \hat{p}(m) \\ &= \Delta p^{'}(m) \end{aligned} \tag{14}$$

$\Delta p^{'}(m)$ 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.

III. Results and Discussion

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, demonstrating 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.

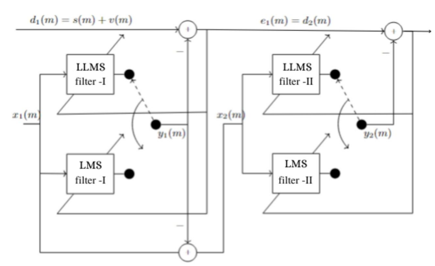

Fig. 1. Switched Adaptive filter Structure

IV. Conclusion

This paper presents a robust method for signal denoising utilizing a switched adaptive filter model based on LLMS and LMS algorithms. The LMS filter's flexibility makes it particularly useful in environments with variable and unpredictable noise patterns. Simulation results highlight that this filter outperforms other adaptive

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 I
COMPARISON OF MSE AND SNR PERFORMANCE USING SDLMS AND SELMS

filter structures, providing a more economical option for reducing noise.

REFERENCES

[1] P. Kumar, K. Nathwani, V. Abrol and S. Kumar, ”Compressive Self-Noise Cancellation in Underwater Acoustics,” Sensor Signal Processing for Defence Conference (SSPD), pp. 1-5, 2022.

[2] Pauline, S.H., Dhanalakshmi, S. and Kumar, R. Variable-Stage Cascaded Adaptive Filter Technique for Signal De-Noising Application. Circuits Syst Signal Process., vol. 41, pp. 1972–2006, 2022.

[3] David Santos-Domínguez, Soledad Torres-Guijarro, Antonio Cardenal-López, Antonio Pena-Gimenez, ShipsEar: An underwater vessel noise database, Applied Acoustics, Volume 113, pp. 64-69, 2016.

[4] S. Dixit, D. Nagaria, Design and analysis of cascaded LMS adaptive filters for noise cancellation, Circuits Syst. Signal Process., vol. 36, no. 2, pp. 1-25, 2017.

[5] A. K. Maurya, Cascade-cascade Least Mean Square LMS Adaptive Noise Cancellation, Circuits Syst. Signal Process., vol. 37, no. 9, pp. 3785-3926, 2018.