PCG Signal Denoising Using Switched Adaptive Filtering Technique with low-Complexity
(B145)

Project Member Details

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Project Guide

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INTRODUCTION

- Phonocardiogram (PCG) signals are recordings of the sounds produced by the heart, typically captured using a stethoscope or a specialised microphone.
- These signals provide critical information about the heart's mechanical activity, such as the opening and closing of valves and blood flow dynamics and is used in diagnosing and monitoring heart conditions, including valve disorders and heart murmurs.
- By analysing the distinct sounds within the PCG—through digital signal processing techniques that examine the timing, frequency, and intensity of heart sounds—medical professionals can accurately identify and interpret cardiac events.

- However, PCG signals are susceptible to noise from various sources, including environmental sounds, body movements, electronic interference, and respiratory noises.
- This noise can significantly affect the accuracy and reliability of PCG analysis.
- Interference can lead to misinterpretation of heart sounds, potentially resulting in misdiagnosis or overlooked conditions.
- Therefore, implementing effective noise reduction techniques, such as filtering and adaptive noise cancellation, is essential to maintain the clarity and usability of PCG signals for precise cardiac assessments.

Motivation & Objectives of the work

- **Accurate Diagnosis**: PCG signals are used to diagnose various heart conditions. Noise can obscure important features in these signals, leading to misdiagnosis or missed diagnosis.
- **Improved Signal Quality**: Noise reduction enhances the clarity of the heart sounds, making it easier for clinicians and automated systems to analyze them.
- **Reliable Feature Extraction**: Many diagnostic algorithms rely on extracting features from PCG signals. Noise can interfere with the accuracy of these features.
- **Automation**: Automated systems for heart sound analysis require clean signals for robust performance. Noise can cause these systems to fail or produce unreliable results.

Objective

- **Objective**:
  Develop an adaptive filter setup for effective noise cancellation, aiming for high signal-to-noise ratio (SNR) and minimal estimation error with a straightforward algorithm.

- **Proposed Solution**:
  Introduce a multi-stage feed-forward switched adaptive filter model designed for active noise control (ANC) systems.

- **Novel Approach**:
  The system automatically adjusts the number of filter stages to enhance performance.

- **Algorithm Innovation**:
  Utilize switching between two signed LMS (Least Mean Squares) algorithms for each filter stage to optimize results.

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 2021 in IEEE Transactions on Signal Processing.	Reconfigurable Filter Design for Multiband Noise Cancellation	This research introduces a reconfigurable filter design that can adapt to different noise bands, improving the versatility and effectiveness of noise cancellation systems in dynamic environments.
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 algorithm for specific use cases.

YEAR AND PUBLICATION	TOPIC	INFERENCE
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.

Problem Statement

Challenges with Traditional Adaptive Filters:

- Difficulty achieving high Signal-to-Noise Ratio (SNR) with low estimation error.
- Slow convergence rates.
- Instability in performance.

Limitations of Existing Filters:

- Fixed-stage filters are not adaptable to varying noise environments.
- Performance is limited due to the inability to adjust filter stages dynamically.

Proposed Solution:

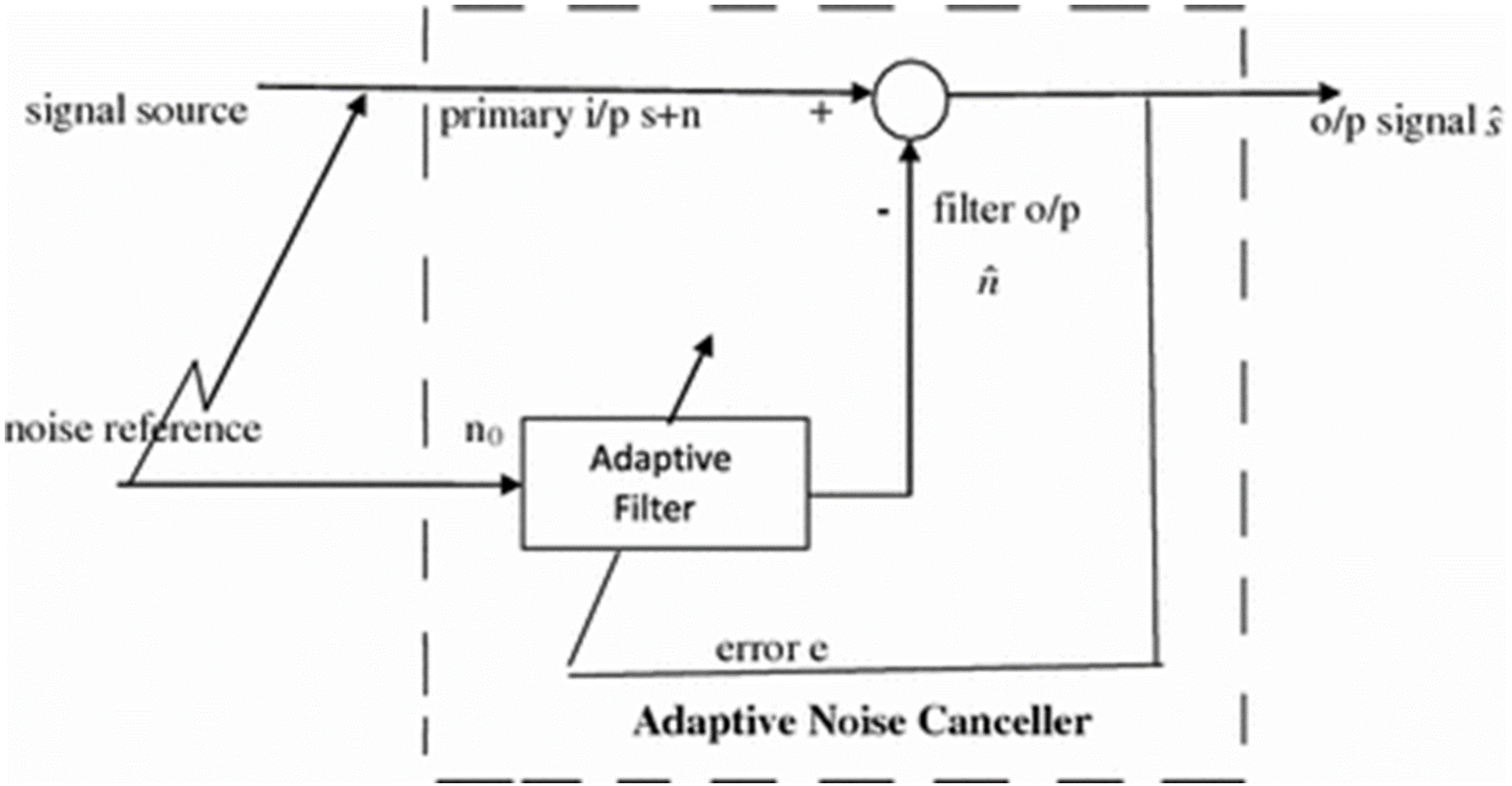
Development of a Multi-Stage Feed-Forward Adaptive Filter:

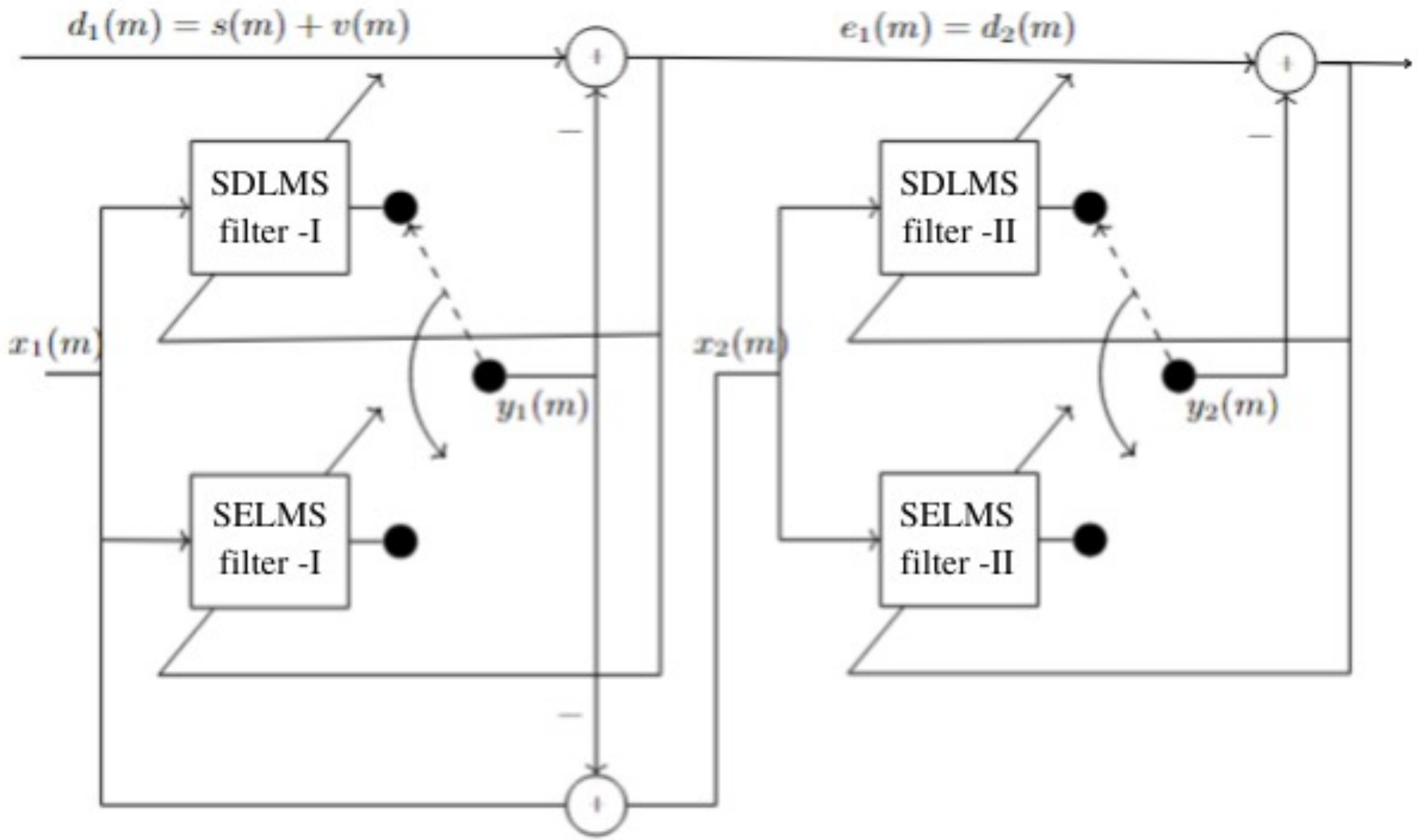
- **Automatic Adjustment of Filter Stages:** The filter adjusts the number of stages automatically to optimize performance.
- **Algorithm Switching:** It switches between two signed LMS algorithms to balance between noise reduction and convergence speed.

Aim of the Work:

- To enhance the efficiency of noise cancellation.
- To improve adaptability in diverse applications, making the filter suitable for varying noise environments.

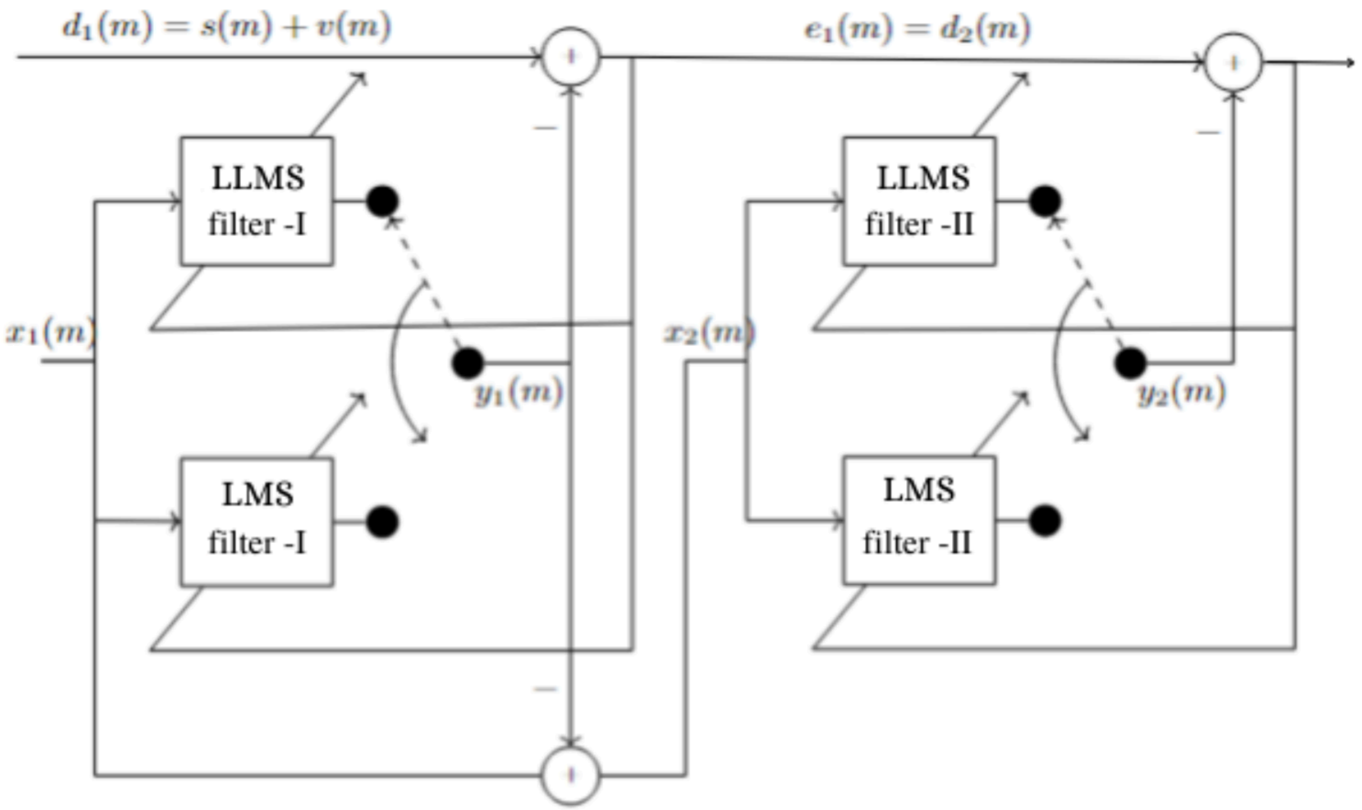
Block Diagram of Adaptive Filter





$d_1(m) = s(m) + v(m)$
$e_1(m) = d_2(m)$
SDLMS filter -I
SELMS filter -I
SDLMS filter -II
SELMS filter -II
$x_1(m)$
$x_2(m)$
$y_1(m)$
$y_2(m)$

Using 2-Stage LLMS and LMS



Why LLMS and LMS ?

- LLMS is an adaptive filtering algorithm that enhances the stability and convergence of the standard Least Mean Squares (LMS) algorithm by gradually forgetting older weights, a feature that enhances its effectiveness in non-stationary environments.

Key features of LLMS & LMS:

- **Adaptability**: Like LMS, LLMS adjusts the filter weights based on the error between the desired and actual outputs, making it suitable for environments where the signal characteristics change over time.
- **Leakage Factor**: The introduction of a leakage factor (typically denoted as α, where $0<\alpha<1$)allows the algorithm to decay the influence of older weights. This helps prevent issues like divergence or slow adaptation in rapidly changing environments.
- **Weight Update Rule**: The weight update formula incorporates the leakage factor, leading to a balance between retaining historical information and adapting to new data.

- LLMS offers a more robust solution for adaptive filtering in dynamic conditions.

NOTES:

- **Initialization**: The choice of initial weights can affect convergence speed but is usually set to zero or small random values.

- **Step Size (μ)**: A critical parameter that influences the convergence speed and stability. It should be chosen carefully, often requiring empirical testing.

- **Leakage Factor (α)**: This controls how quickly the older weights are "forgotten." A higher value leads to faster adaptation but may destabilize the filter if too high.

Leaky Least Mean Squares (LLMS) algorithm in a tabular format, outlining the key steps involved in the process:

Description	Equation/Concept
Initialize weights	$w[0]=0$ or small random values
Set parameters	Choose step size μ and leakage factor α ($0<\alpha<1$)
For each iteration n	- Repeat steps 4 to 7 for each input sample
Compute the output	$y[n]=w[n]^T x[n]$
Calculate the error	$e[n] = d[n] - y[n]$
Update weights	$w[n+1] = (1- \alpha)w[n] + \mu e[n]x[n]$
Optionally, store error or output for analysis	Keep track of e[n] r y[n] as needed

Proposed approach

- For Stage I ANC, the initial input is $d1(k)=s(k)+c(k)$
and the reference input is the noise signal $c'(k)$.
- The erroneous signal from the previous ANC stage serves as the input for the current stage.
- The noise from the previous ANC stage is used as the reference noise for the current stage.
- The design incorporates feed-forward SDLMS and SELMS adaptive filters with filter coefficients updated using the Sign Data LMS algorithm.
- Weights are adjusted based on the error from the previous stage and the difference between the output and input of the previous stage filter.

- 2nd Stage is controlled automatically, based on the correlation between the output error of the current stage and the standard noise.
- If the error is minimally correlated with $c'(k)$, no additional stage is added.
- The optimal condition is where there is no correlation between $e(k)$ and $c'(k)$, resulting in minimal noise in the final output.
- The step size is adjusted according to the autocorrelation of the inbound signal.
- Inputs at the final stage L are processed based on the described mechanism and adjustments made throughout the stages.

Realistic Constraints

- **Slow Convergence**: Adaptive filters converge slowly if initial coefficients are far from optimal.
- **Step Size Sensitivity**: Stability and convergence depend on the step size; too large can cause instability, too small results in slow convergence.
- **Input Signal Properties**: The filter's performance is affected by input signal characteristics like autocorrelation and noise.
- **Trade-offs**: A larger step size speeds up convergence but may cause instability; a smaller step size enhances stability but slows convergence.

Results

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**

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Table 2. MSE, SNR and ANR for different AF structures: Pathological PCG

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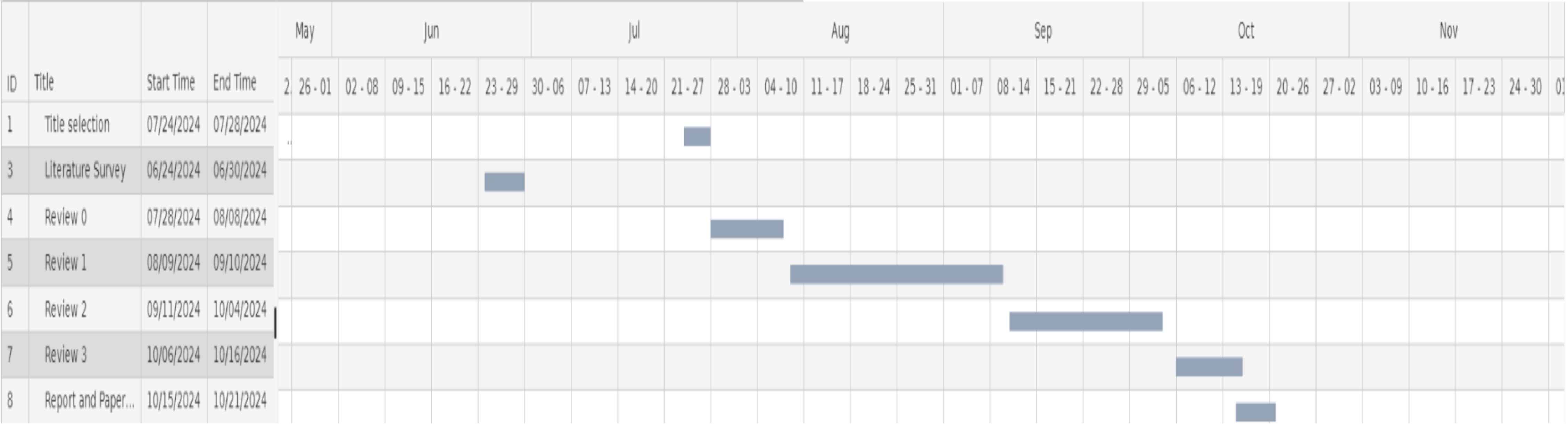
Time & Action Plan (Gantt Chart)

Minor Project Timeline (B145)



ID	Title	Start Time	End Time
1	Title selection	07/24/2024	07/28/2024
3	Literature Survey	06/24/2024	06/30/2024
4	Review 0	07/28/2024	08/08/2024
5	Review 1	08/09/2024	09/10/2024
6	Review 2	09/11/2024	10/04/2024
7	Review 3	10/06/2024	10/16/2024
8	Report and Paper...	10/15/2024	10/21/2024

References

1. H. Deng and M. Doroslovacki, "A New Adaptive Noise Cancellation Scheme for Speech Enhancement," IEEE Transactions on Signal Processing, vol. 53, no. 7, pp. 2341-2351, July 2005, doi: 10.1109/TSP.2004.831255.

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

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