Leaky LMS algorithm based low complexity adaptive noise cancellation

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Introduction

Focus of the Project:

The main focus of the project is denoising and analysis of acoustic signals (i.e Speech signal) using the Leaky LMS Adaptive Filtering Algorithm.

Importance of the signals:

- Speech signals are crucial for detecting speech disorders as they reveal slight problems in a person's voice that indicate underlying speech and Neurological disorders .
- Speech signals are essential for both speech recognition and communication.

Introduction Cont.

- The difficulty is that all of these signals are susceptible to noise, which compromises their utility and interpretation.
- The Leaky LMS adaptive filtering technique is suggested as a way to effectively reduce noise while maintaining signal quality.

Motivation & Objectives of the work

- The accuracy of speech signals in medical diagnostics is affected by noise.
- Speech-processing systems perform worse when speech signals are distorted.
  - Techniques like wavelet transforms, deep learning and EMD work but are computationally expensive and unsuitable for real-time systems.
- Current approaches are too complicated and computationally demanding for real-time applications.

Motivation & Objectives Cont.

Objective:

- To design and implement a computationally efficient Leaky LMS adaptive filtering algorithm for denoising.

- Improve signal clarity while preserving its original characteristics.

Novelty

- Use of Leaky LMS in multistage model

- Weight update equation of LMS:

$$w(n+1) = w(n) + \boldsymbol{\mu} e(n) x(n)$$

- Weight update equation of Leaky LMS:

$$w(n+1) = (1 - \mu\gamma)\mathbf{w}(n) + \mu e(n)\mathbf{x}(n)$$

where:

$0 < \gamma << 1$

- The leakage term γ is a parameter which controls how much current weight vector w(n) is reduced during each update.

Need for Leaky LMS

- In normal LMS algorithm, weights are updates purely based on the error signal e(n) and the input signal x(n).
- If the error is large, or if the input signal has very high noise, the weights may grow too much leading to instability.
- So, the normal LMS algorithm has no mechanism to prevent the weights from growing too large, leading to instability in some situations.

- In the Leaky LMS, the Leakage term acts as a damping or controlling factor, reducing the weights slightly at each iteration.
- Weights are controlled so the convergence is smooth with good stability, especially in signals with high noise.

Literature Survey

YEAR AND PUBLICATION	TOPIC	INFERENCE
Published in 2023 in IEEE.	Hardware Co-Simulation of Adaptive Noise Cancellation System using LMS and Leaky LMS Algorithms	This paper discusses the co-simulation approach for implementing adaptive noise cancellation using LMS and Leaky LMS algorithms, showing improved noise cancellation efficiency when implemented in hardware setups like FPGA.
International Journal of Electronics and Communications, 2022,	Implementation of Optimized Adaptive LMS Noise Cancellation System to Enhance Signal to Noise Ratio	The paper focuses on optimizing the LMS algorithm to improve the signal-to-noise ratio (SNR) in communication systems, demonstrating significant performance enhancements in various noise environments.
Journal of Signal and Information Processing,2023.	A Comparative Study on Characteristics and Properties of Adaptive Algorithms applied to Noise Cancellation Techniques	This study compares various adaptive algorithms like LMS, RLS, and NLMS, analyzing their strengths and weaknesses in noise cancellation applications, providing insights into selecting the most suitable algorithm for specific use cases.
Journal of Circuits, Systems, and Signal Processing,2024.	A Switching-Based Variable Step-Size PNLMS Adaptive Filter for Sparse System Identification	A switching-based variable step-size PNLMS algorithm is proposed to improve convergence in sparse system identification, adjusting the step-size dynamically for faster and more stable performance. A sub-band version is also introduced for correlated inputs, showing better convergence than existing methods.

Problem Statement

Noise in speech Signals:

- Ambient interference reduce diagnostic accuracy.

Challenges in Speech Signal Processing:

- Background noise and channel distortions affect speech recognition and synthesis.

Problem Statement Cont.

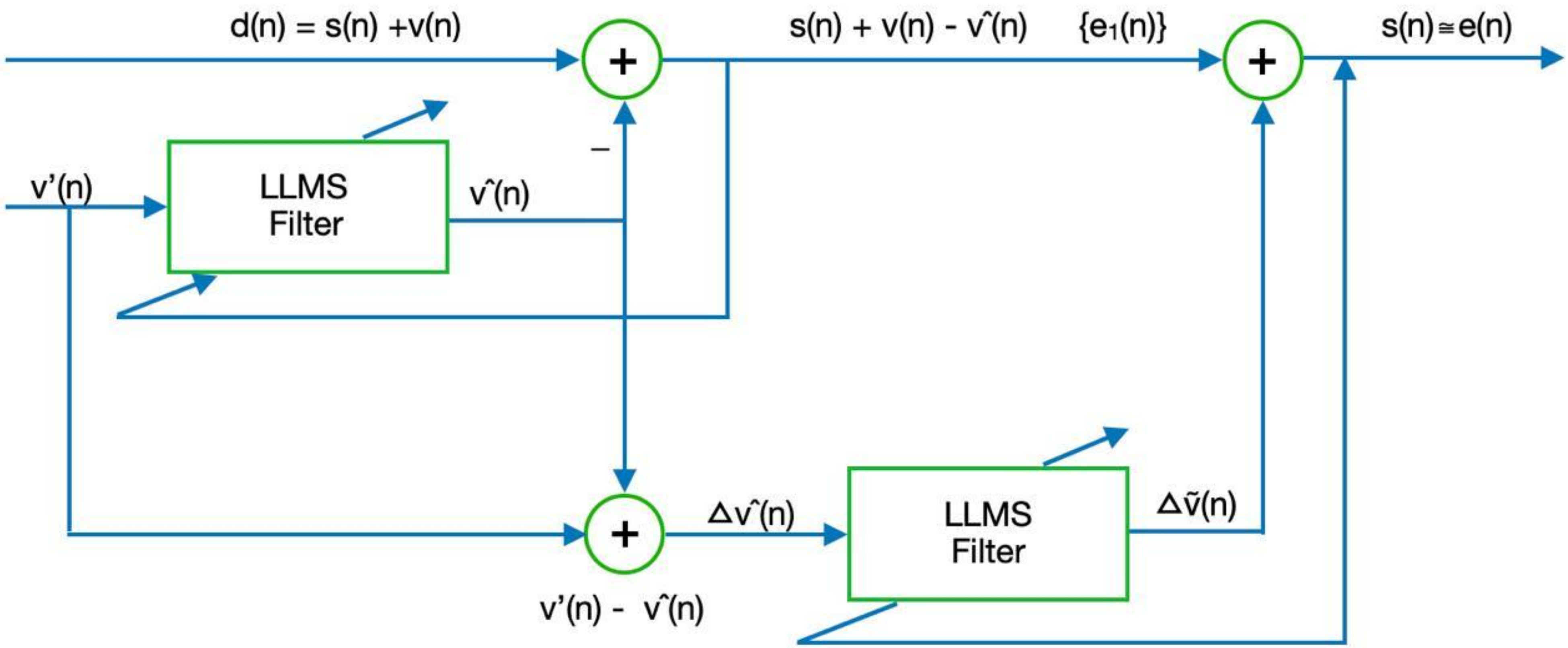
Existing Solutions:
Techniques like wavelet transforms, deep learning and EMD work but are computationally expensive and unsuitable for real-time systems.

Proposed Solution:

The Leaky LMS Adaptive Filtering Algorithm provides good convergence and enhanced noise suppression with **low complexity**.

Block Diagram

- Proposed 2-stage Leaky LMS Adaptive Filter



Algorithm.

1st stage :

- The clean speech signal is denoted as : $\boldsymbol{s}(n)$
- The noise signal added to the clean signal : $\boldsymbol{v}(n)$
- Noise added Input signal: $d_1(n) = \boldsymbol{s}(n) + \boldsymbol{v}(n)$
- Reference noise signal: $x_1(n) = v'(n)$

- Output signal from the 1st stage of the LLMs filter:
  $y_1(n) = w_1^T(n)x_1(n) = \hat{v}(n)$

Algorithm.

- The weights gets updated as follows:

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

$$= \ (1 - \mu\gamma)w_1(n) + \mu[d_1(n) - x_T(n)w_1(n)]x(n)$$

- Error signal: $e_1(n) = d_1(n) - y_1(n) = s(n) + v(n) - \hat{v}(n) = s(n) + \Delta v(n)$
- Leakage factor: Where γ is the leakage component in the equation.

  μ is the represents the step-size of Leaky LMS filter.

Algorithm.

2nd stage :

- The Input signal to the 2nd stage of the filter is :

$$d_2(n) = e_1(n) = s(n) + v(n) - \hat{v}(n) = s(n) + \Delta v(n)$$

- Reference signal to the 2nd LLMS Filter:

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

- Output of the 2nd LLMS filter : $y_2(n) = \mathrm{w}_2^T(n)\Delta v'(n) = \Delta\hat{v}(n)$
- The output error signal corresponds to:
- $$e_2(n) = \mathrm{s}(n) + v(n) - \Delta\hat{v}(n) \approx s(n)$$

Algorithm.

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

- Noise added Input signal: $d_1(n) = \boldsymbol{s}(n) + (n)$
- Reference noise signal: $x_1(n) = v'(n)$
- Output signal from the 1st stage of the LLMs filter: $y_1(n) = w_1^T(n)x_1(n) = \hat{v}(n)$
- The weight update of the filter

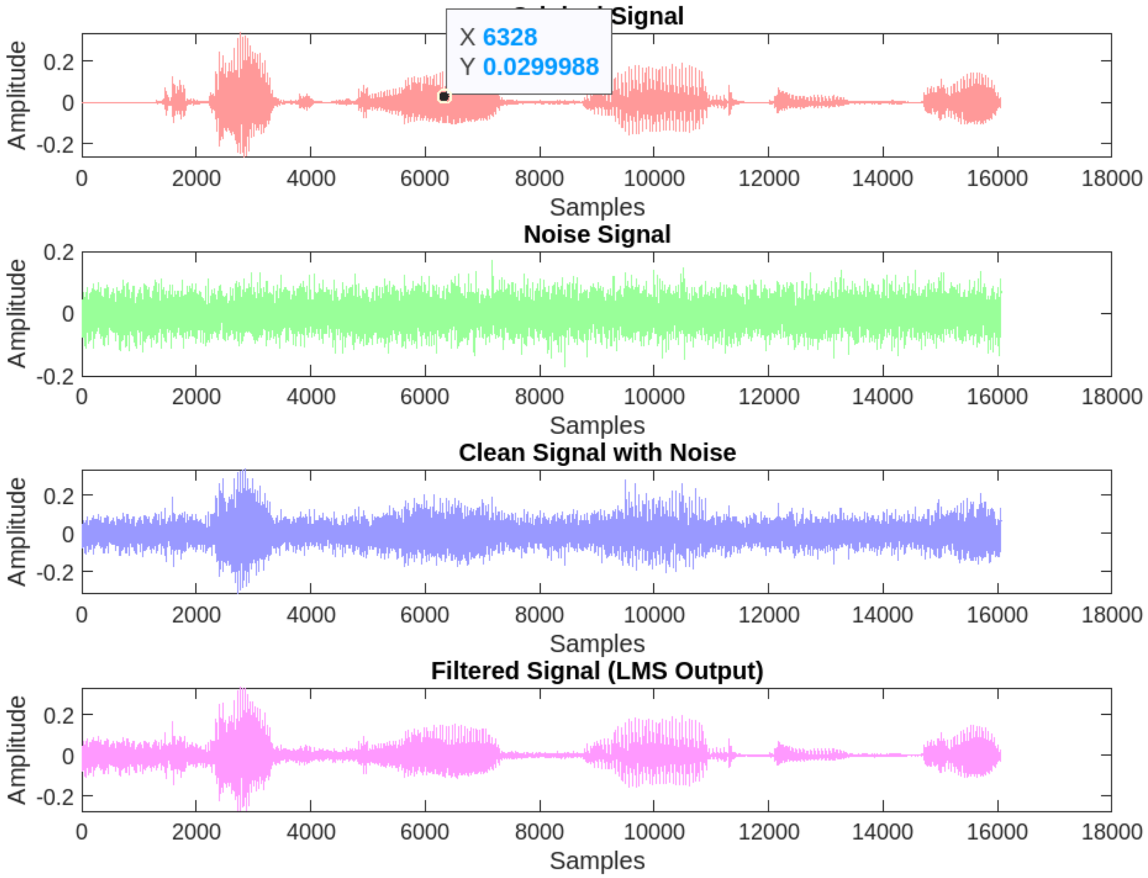
$$w_1(n+1) = w_1(n) + \mu e_1(n)v'(n)$$

Program algorithm

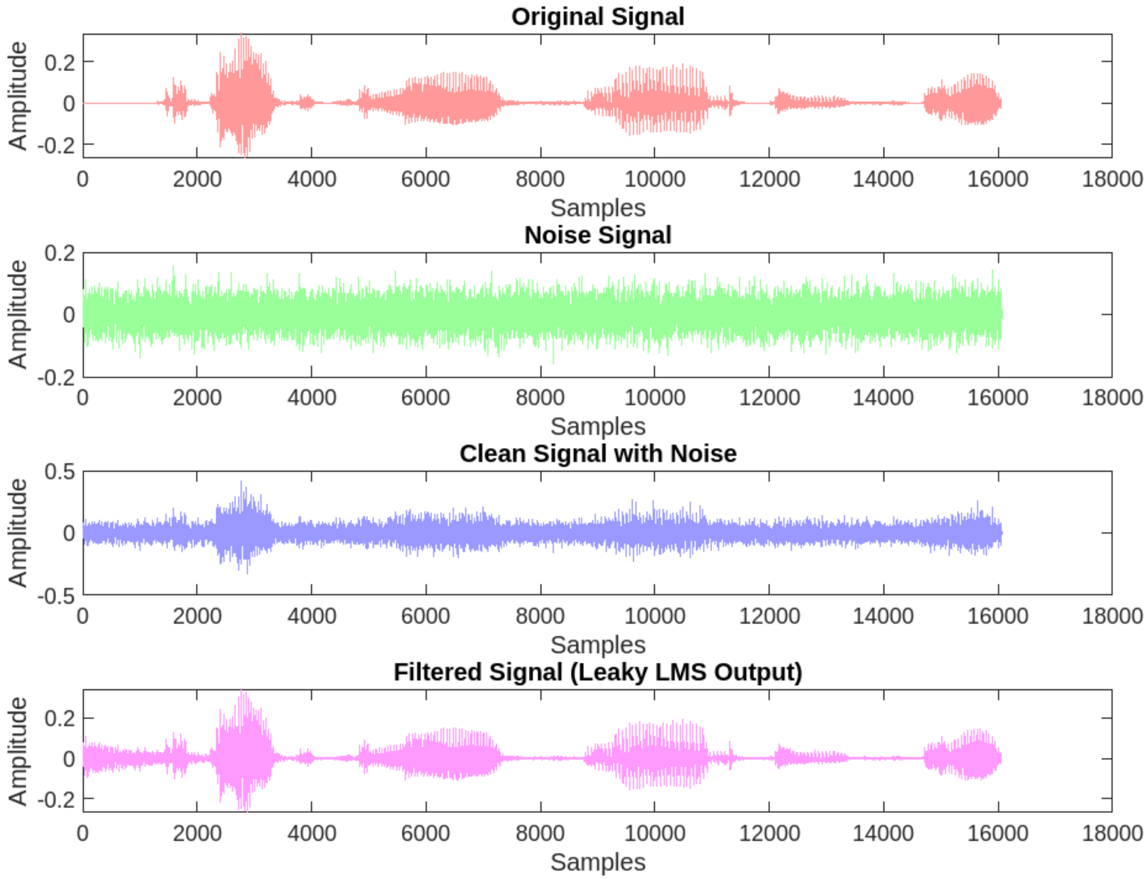
- Step 1: **Load Signals-**
  - Load the speech/PCG audio file (theoretically includes a clean signal for MSE & SNR calculations).
  - Add noise (Gaussian/Uniform/Street) to create the noisy signal.
- **Step 2: Call the 2 Stage Leaky LMS**
  - Specify parameters: input/desired signals, step size, filter order, leakage factor, and number of stages.
  - Run the 2-stage leaky LMS function.
- **Step 3: Generate Plots & Compute Metrics**
  - Plot the original signal, noise, noisy signal, and the filtered output.
  - Calculate MSE & SNR using the clean signal, noisy signal, and the filtered (error) signal.

Results

SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1

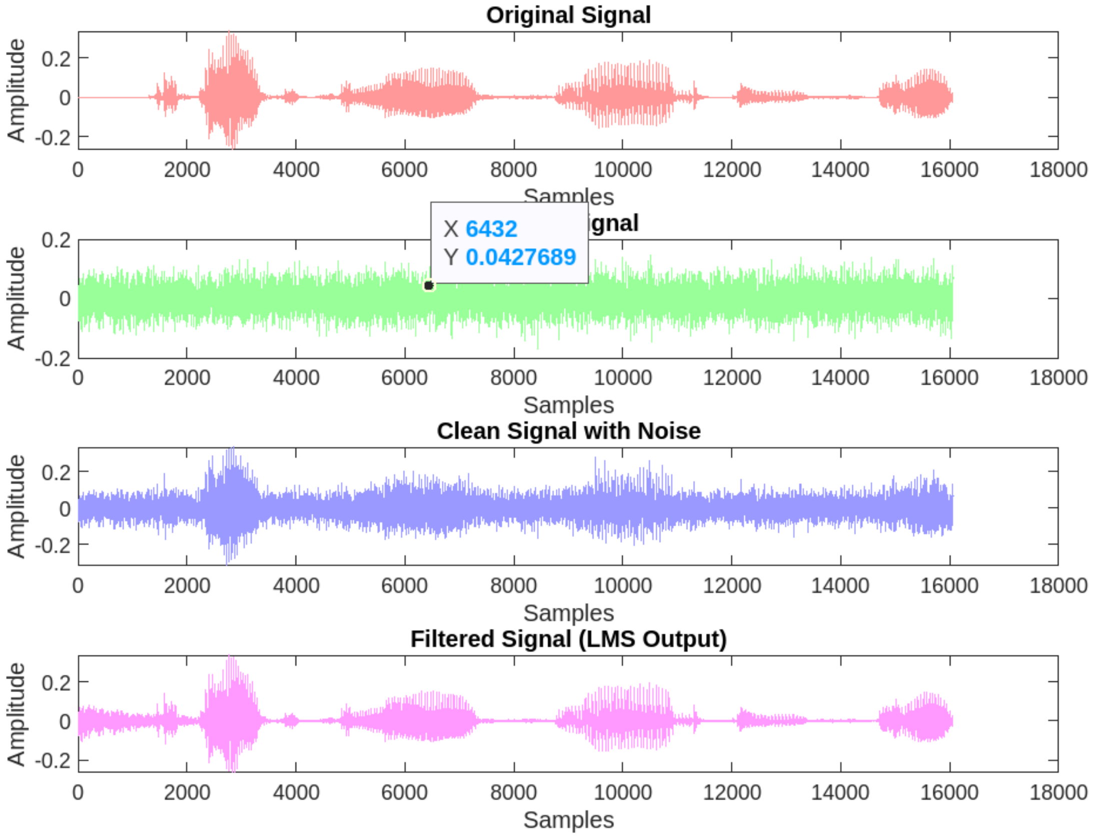


SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1

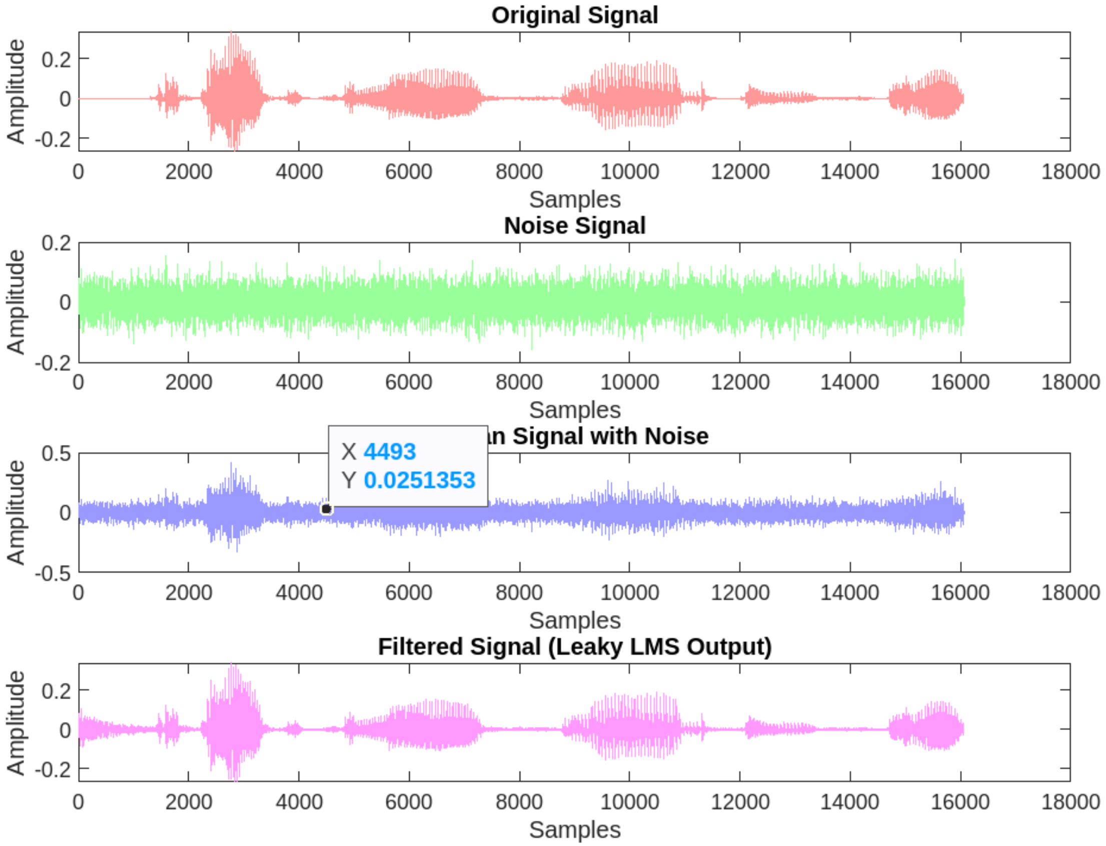


Results

SPEECH SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 2

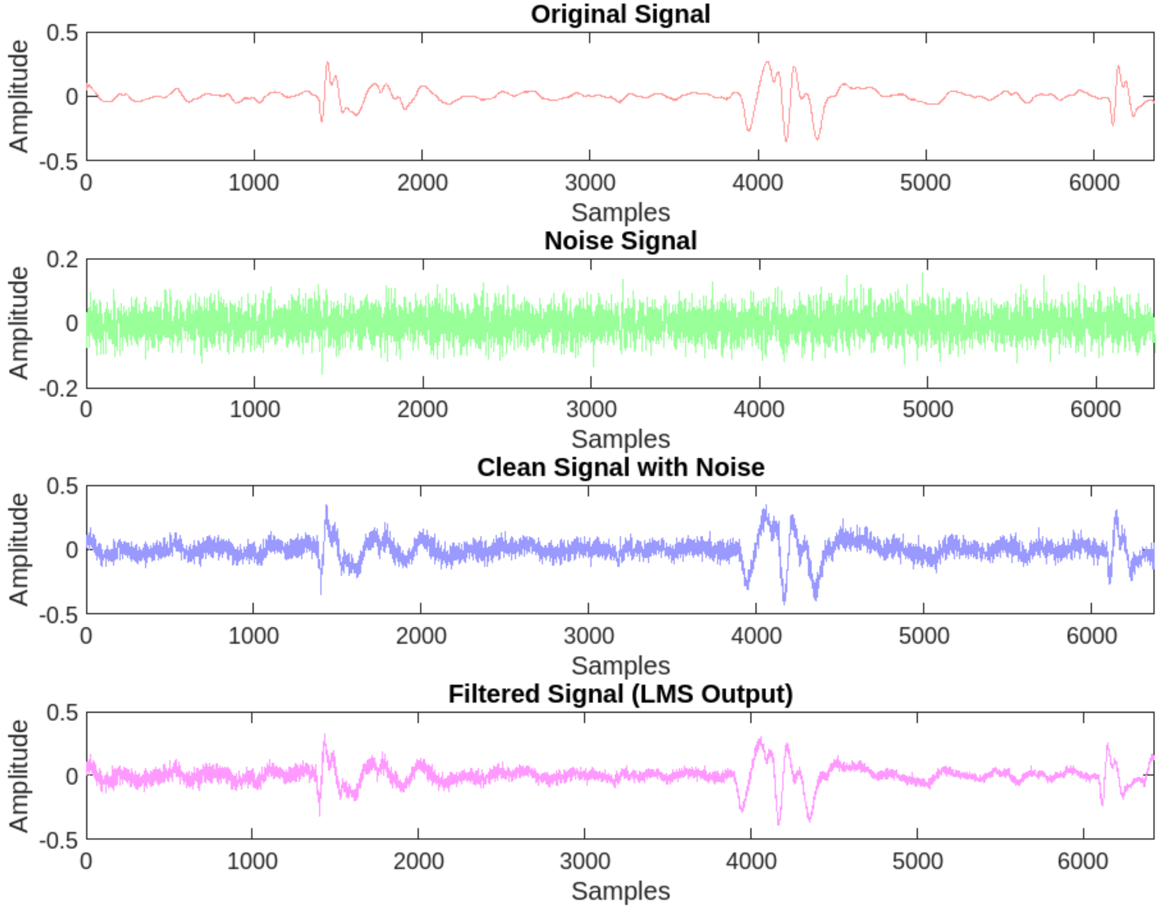


SPEECH SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 2

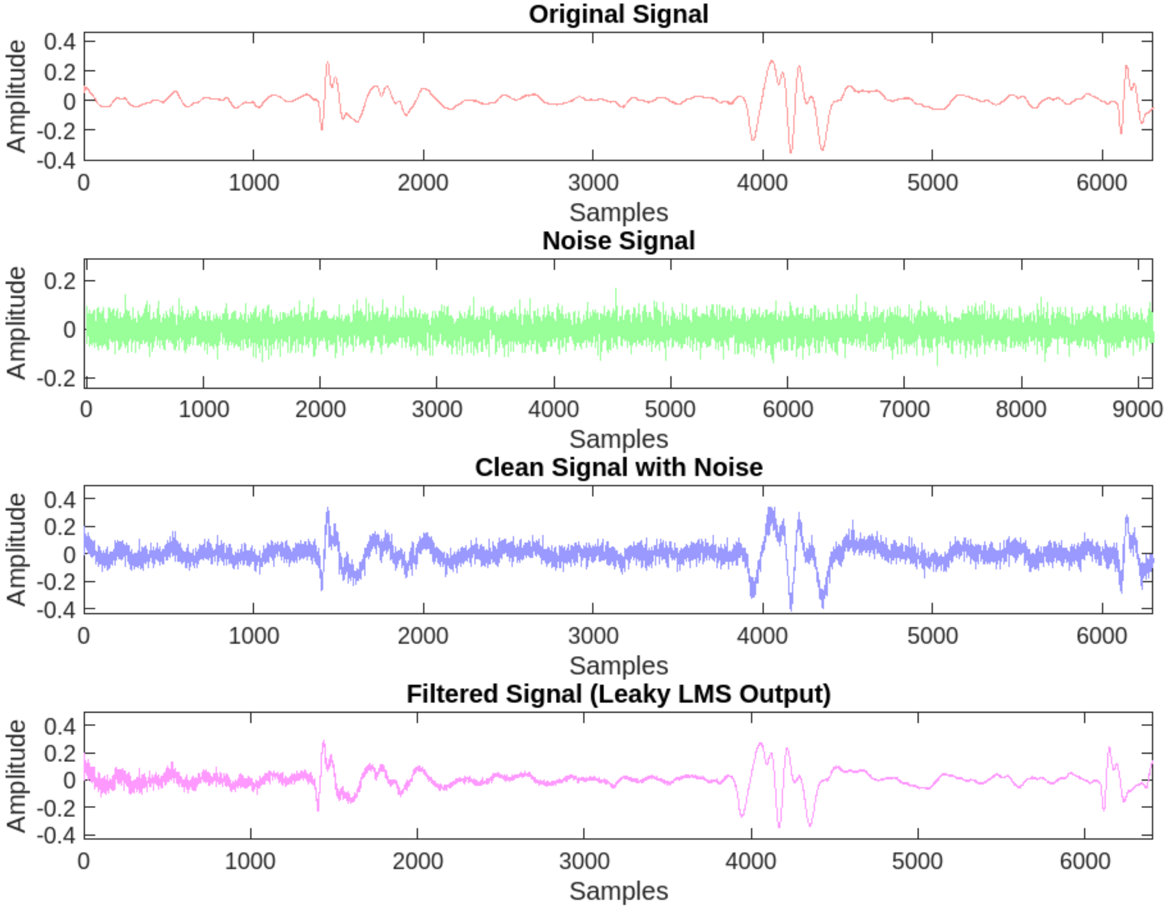


Results

PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 1

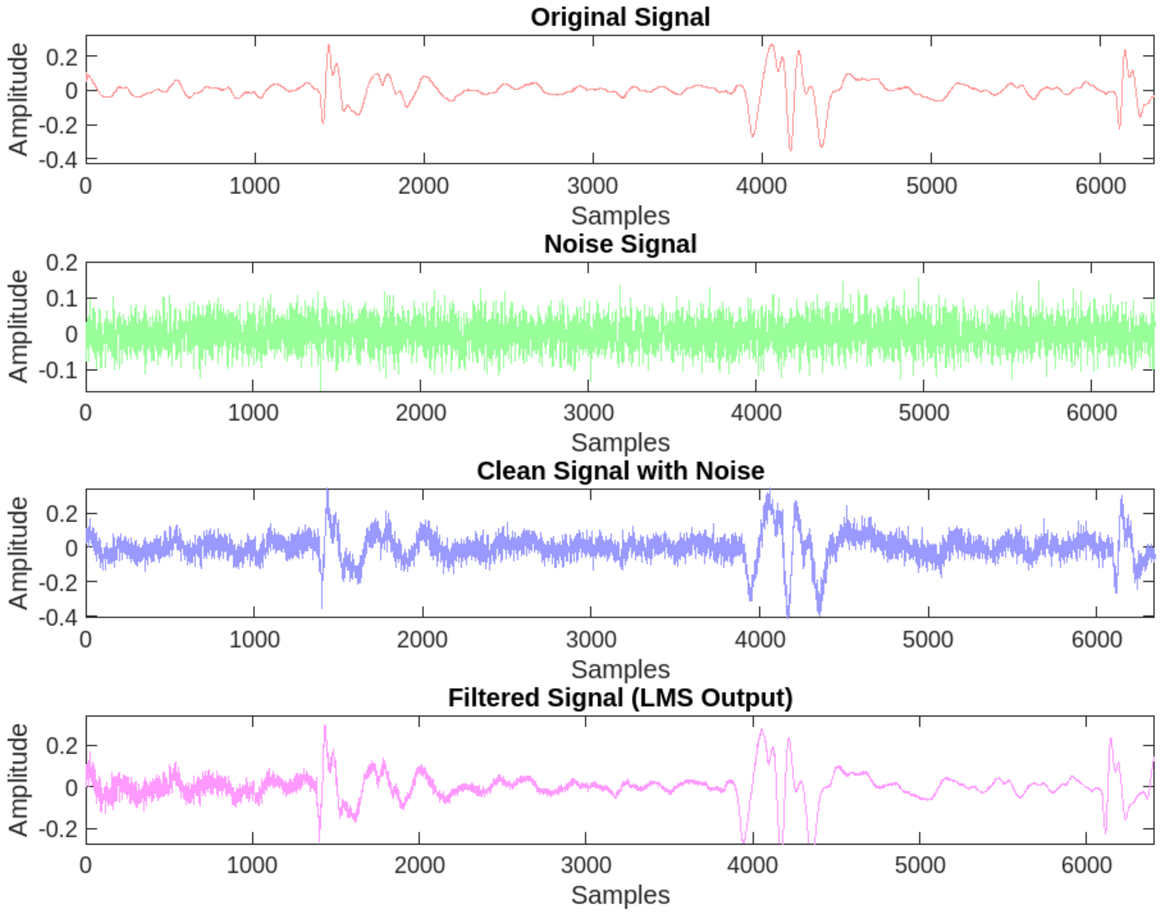


PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 1

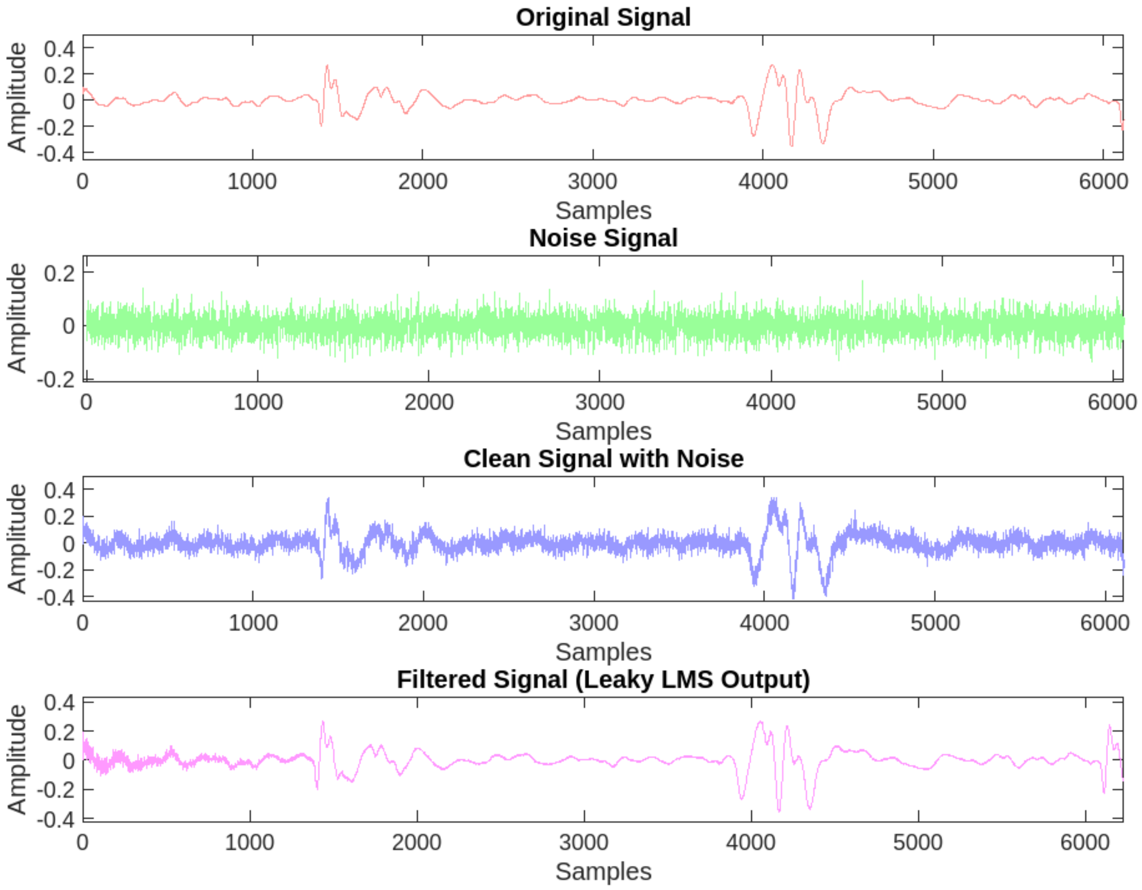


Results

PCG SIGNAL WITH GAUSSIAN NOISE USING LMS – Stage 2



PCG SIGNAL WITH GAUSSIAN NOISE USING LEAKY LMS – Stage 2



Results

Input SNR: 5 dB

Signal Type	MSE	SNR
SPEECH+GAUSSIAN stage1 LMS	MSE: 0.0023854	SNR: 10.2981 dB
SPEECH+GAUSSIAN stage2 LMS	MSE: 0.00014043	SNR: 12.616 dB
SPEECH+GAUSSIAN stage1 LLMS	MSE: 0.0015931	SNR: 16.8809 dB
SPEECH+GAUSSIAN stage2 LLMS	MSE: 0.00017979	SNR: 18.728 dB

Results

Input SNR: 5 dB

Signal Type	MSE	SNR
PCG+GAUSSIAN stage1 LMS	MSE: 0.0024509	SNR:9.2879 dB
PCG+GAUSSIAN stage2 LMS	MSE: 0.00017721	SNR: 11.072 dB
PCG+GAUSSIAN stage1 LLMS	MSE: 0.00010121	SNR: 12.8636 dB
PCG+GAUSSIAN stage2 LLMS	MSE: 8.322e-05	SNR: 13.7235 dB

Realistic Constraints

- **Economic Constrains**:
  The project demands significant processing power, which increases the cost, particularly for systems that need real-time capabilities.
- **Environmental Constrains** :
  The performance of the system can be influenced by environmental factors, such as fluctuating noise levels, signal interference, and changing conditions, which could affect the consistency and quality of the results.
- **Social Constrains** :
  This project positively impacts communication, safety, and accessibility. It helps society by improving speech recognition, enhancing noise detection, and providing better audio diagnostics for medical applications and other fields.
- **Ethical Constrains** :
  There are no ethical issues or concerns associated with this project.

Realistic Constraints Cont.

- **Health and Safety Constrains** :
  The project does not pose any health or safety risks.

- **Manufacturability Constrains** :
  The system can be fabricated and replicated using Field Programmable Gate Arrays (FPGAs).

- **Sustainability** :
  Materials used in the project, including printed circuit board components, solder, and integrated circuits made from silicon and epoxy packaging, are largely non-recoverable, which may have an impact on resource sustainability over time.

Engineering Standards

- IEEE 802.11 (Wi-Fi Standards): Defines methods for signal processing in wireless communication, ensuring effective filtering and noise management in networks.
- IEC 61672 (Electroacoustic Measurement Standards): Provides guidelines for measuring the performance of audio and acoustic signal processing equipment, which is essential for filter accuracy.
- ISO 9001 (Quality Management): Ensures that signal processing systems, including adaptive filters, meet consistent quality standards for reliability and performance.

References

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

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

Time & Action Plan (Gantt Chart)

REVIEW NUMBER	DATES	Remarks
Review 0	**21 Dec 24**	Title Confirmation
Project Timeline & Work plan	**09 Jan 2025**	Engineering standards and Realistic Constraints
Review 1	**24th to 30th Jan 2025**	Study of different signals and noise, LMS algorithms and Implementation of two stage Leaky LMS
Review 2	**4th to 10th March 2025**	Implementation of Leaky LMS Multistage
Review 3	**2nd to 8th April 2025**	Implementation of Recursive Leaky LMS
Poster and Demo	**4th to 10th March 2025**	
Report Submission	**28^{th} April 2025**	