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SIMULATION AND COMPARATIVE ANALYSIS OF AN ENHANCED NOISE CANCELLATION IN ECG SIGNAL DENOISING VIA NORMALIZED LEAST MEANS SQUARE (NLMS) ALGORITHM

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Abstract
The clinical utility of ECG signal can be compromised by the presence of unwanted components and interference in the ECG signals which do not only obscures critical cardiac information but also introduces inaccuracies in the analysis, leading to misdiagnoses and suboptimal patient care. However, noise in ECG signals arises from multiple sources, including muscular activities, baseline wanders, power line interference and electrode artifacts. This work propose a robust enhanced filtering techniques using the Normalized Least Means Square (NLMS) Algorithm designed to successfully cancel noise out of ECG signal while preserving the key diagnostic features. Extensive simulations were conducted using standard PhysioNet ECG Database and the Massachusetts Institute of Technology- Beth Israel Hospital (MIT-BIH) Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database, and the MIT-BIH QT Database to validate performance across diverse noise condition. In the most challenging scenario, where the input Signals-to-Noise (SNR) reached as low as -5 dB, the filter achieved a SNR output quantifying approximately 88.96dB. The filter across different noise type, ECG datasets, and signals-to-noise ratio (SNR) levels suggest that the enhanced filtering approach has potential for broader applicability in various clinical contexts and can be integrated into a diverse array of monitoring system.
Keywords: *Electrocardiographic Signals, Normalized Least Means Square (NLMS) Algorithm, Simulations, ECG Denoising, MIT-BTH.*

Introduction

ECG are used to measure the rate and rhythm of heartbeats, the size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, the effects of heart drugs, and the function of implanted pacemakers (Braun Wald and Eugene, 1997). To check the electrical activity of the heart using electrocardiogram (ECG) signals is one of the well-known ways to diagnose arrhythmias.

Due to the role of ECG signal in providing information on the diagnosis and treatment of heart disease, the issue of cardiac signal acquisition and its consequent analysis has been studied as a significant concern for cardiologists since many years ago. The main problem in the processing of this signal is the extraction of a series of physiological or non-physiological features

Electrocardiographic machines

Electrocardiographic machines (ECG or EKG machines) are medical devices used to record the electrical activity of the heart. It detects the tiny electrical signals produced when the heart beats and displayed them as waves on paper or a screen. These pattern of the waves helps doctors understand heart rhythm and functions. ECG machine involves the Electrodes – including small metal or sticky pads placed on the chest, arms, and legs, Lead wires – that connects the electrodes to the machine, Amplifier – which strengthens the heart's electrical signals and Display/Recorder that shows or prints the ECG tracing.

Electrocardiographic (ECG) signals are weak non-stationary signal which are interfered by various noise. Sarang *et, al* (2013). These signals are often contaminated by noise from diverse sources and forms. Some of them are: 60Hz power line interference that overlaps with the ECG spectrum, motion artifact from the electrode–skin interface, muscle activities affecting the high content of the ECG signals etc. ECG signal denoising is the process of separating the actual signal component from undesired signals to obtain noise free ECG that facilitates easy and accurate diagnosis. A denoising approach should detect the different noises in the data and filter the data while ensuring the key features of obtained results are not influenced by undetected artifacts.

To mitigate the impact of noise on ECG signals, numerous techniques have been proposed, various noise reduction techniques, which includes analog filtering and early digital filtering methods but they often lack the flexibility and adaptability required to effectively handle complex noise scenarios and diverse patient populations. Furthermore, the existing noise filtering approaches may inadvertently alter or distort important features of the ECG signal, potentially leading to erroneous diagnoses and treatment decisions. Uzoamaka *et. al* (2025).

Some of the approaches used for de-noising the ECG signal includes the adaptive filtering algorithm, Cascaded Adaptive Nosie Cancellation (CANC) technique to eliminate major noise source (Alla and Nayak, 2024), Wavelet Packet transform (WPT) that uses the synlets and mother wavelet to decomposed ECG data (Mir and Singh, 2024), Artificial Bee Colony (ABC) Adaptive filtering Algorithms that approach ECG signals with different types of thresholding techniques (Verma et al, 2016), and many others. But, one of the primary distinctions that sets the Normalized Least Means Square (NLMS) Algorithm apart from its traditional counterpart, the Least Mean Squares (LMS) algorithm, Recursive Means Square (RMS) Algorithm is its implementation of normalization within the coefficient update process. This normalization serves a critical function by preventing the divergence of the filter's coefficients, particularly in environments characterized by rapid variations in signal levels or in the presence of noise. As a result, the NLMS algorithm typically exhibits superior convergence properties compared to the LMS algorithm, making it particularly applicable in scenarios where signal dynamics are unpredictable or highly variable. Uzoamaka *et. al* (2025)

In general, the signal processing algorithms employed for denoising, provides optimal performance and eliminates the high frequency noise between any two beats contained in a continuous ECG signal. Despite their optimal performance, the signal processing algorithms significantly attenuate the peaks of characteristics wave of the ECG signal and preserve the morphology of the ECG signals.

Methodology

1. **General systems design** which combines the embedded technology, digital signal processing technology and signal acquisition technology in one
2. **System Hardware Design**; Choice of processor and human-machine interaction interface, including processing speed, complexity of the completed tasks, complexity of peripheral circuits, production costs and high-power consumption
3. **System Circuit Design**; Pre-amplifier circuit, Right leg driver circuit, and Power circuit.
4. **System software design** comprising the lower computer software that completes the acquisition of ECG signals, signal filtering, modules and so on. Also, the upper computer software that complete the reception and processing of data

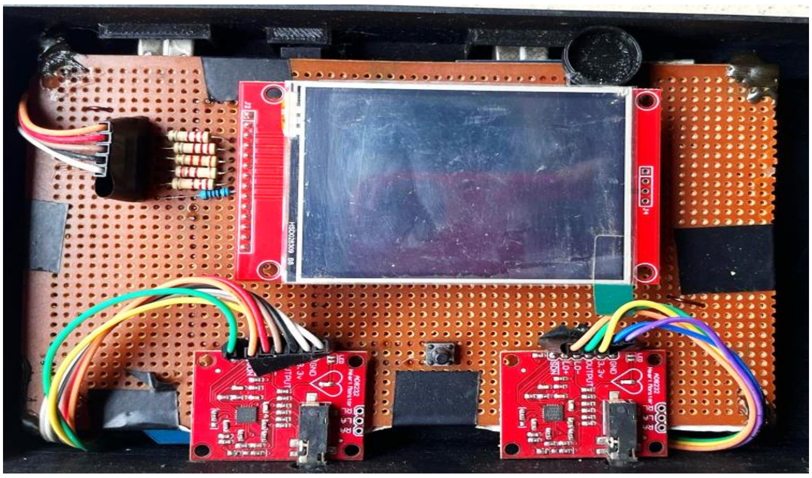

Figure 1. Inner view of the adaptive filter

Signal Modeling: Identifying and characterizing the noise sources present in ECG signals and this identification of these noise characteristics informs the design parameters for the adaptive filter, ensuring that the filter not only attenuates unwanted components but also preserves the morphology of key ECG features (e.g., QRS complex, T-wave).

Signal processing

The following steps were carried out in the signal processing:

i. **Initialization:** The filter coefficients $(w(i))$ would be initialized with zeros. So, at the beginning, the filter coefficients are:

$$w(0) = 0, w(1) = 0$$

ii. **Filtering Process:** The next step is to apply the adaptive filter to the noisy ECG signal (x(n)) using the following equation as adapted from the equation below.

$$y(n) = \sum_{i=0}^{M-1}[w(i) * x(n-i)]$$

iii. **Update Rule (NLMS):** The NLMS algorithm updates the filter coefficients using the following formula at each iteration:

$$w(i, n+1) = w(i, n) + \mu * e(n) * x(n-i) / (\sigma\text{^}2 + \varepsilon)$$

The adaptation step size is critical in determining the speed of convergence and to also ensure that vital information is not clipped out of the original signal. Due to the problem of the traditional real-valued LMS algorithm, this work employs a sigmoid function to establish the non-linear relationship between the step size and the error signal as an improvement to the conventional algorithm. (Qin and Ouyang, 1997):

$$\mu_i = \rho\left(\frac{1}{1 + exp^{(-\alpha|e(n)|)}} - 0.5\right)$$

Where ρ determines the range of values of this function and α controls the shape of this function. Note that $\rho > 0$ and $\alpha > 0$. in the actual implementation of this work, it was observed that as the value of step size decreases, the convergence speed to optimal values is slower and for large values, the filters will diverge and become unstable. So the range of the step-size is peg to $0 < \rho < 1$.

iv. Repeat:

The above steps are repeated for subsequent iterations until the error signal $(e(n))$ converges to a small value, indicating effective noise reduction.

By iteratively adjusting the filter coefficients based on the input signal and error, the adaptive filter adapts to changing noise conditions and optimizes noise reduction performance. In this simplified example, the filter coefficients using a fixed adaptation step size were updated, but in practical implementations, the step size is dynamically adjusted using equation below to achieve better convergence and stability.

$$\mu_i = \rho\left(\frac{1}{1+exp^{(-\alpha|e(n)|)}} - 0.5\right)$$

The result is an estimated denoised ECG signal (y(n)) that minimizes the difference between the noisy ECG signal (x(n)) and the desired noise-free ECG signal (d(n)), effectively reducing noise while preserving essential cardiac information for accurate clinical analysis.

3 Simulation Results and Performance Analysis

A comprehensive simulation studies were conducted to thoroughly evaluate the effectiveness and robustness of the developed adaptive ECG filtering technique. To closely replicate realistic scenarios, the original ECG signals are artificially contaminated by introducing a well-characterized sources of noise typically encountered in clinical ECG recordings. These include power-line interference at 60 Hz, electromyography (muscle) artifacts, electrode-motion artifacts, and baseline wandering. These noisy ECG signals are generated at various predefined input Signal-to-Noise Ratios (SNR), specifically at levels of -5 dB, 0 dB, 5 dB, and 10 dB, providing a diverse spectrum of contamination scenarios for evaluation.

To validate the performance of the developed adaptive filtering technique, A rigorous performance against several state-of-the-art filtering methods, previously reported in the literature were compered. The compared methods include the Cascaded Adaptive Nosie Cancellation (CANC) technique (Alla & Nayak, 2024), the machine learning inspired Artificial Bee Colony (ABC) adaptive filtering method by Verma *et al.*, (2016) and the Wavelet Packet Transform (WPT)-based denoising approach extensively studied by Mir and Singh, (2024). Each of these methods represents a category of noise suppression techniques widely accepted in biomedical signal processing—adaptive filters, met heuristic optimization-based filters, and wavelet decomposition-based approaches.

To ensure consistency and fairness in the comparison, all methods were tested under identical computational conditions, using the same input signals, noise types, and performance assessment procedures. This methodological consistency ensures that observed performance differences accurately reflect the inherent characteristics and capabilities of each filtering technique.

4. Comparison

The detailed comparative performance results obtained through the simulations on Jupyter notebook using the obtained results were presented below and the compared methods includes the Cascaded Adaptive Nosie Cancellation (CANC) technique (Alla & Nayak, 2024), the machine learning inspired Artificial Bee Colony (ABC) adaptive filtering method by Verma *et al.*, (2016) the, Wavelet Packet Transform (WPT)-based denoising approach extensively studied by Mir and Singh, (2024). These evaluation were carried out using the standard ECG signals obtained from publicly available databases, specifically the MIT-BIH Arrhythmia Database (MITDB), MIT-BIH Normal Sinus Rhythm Database (NSRDB) and the MIT-BIH QT Database (QTDB). These are widely recognized benchmarks for evaluating ECG signal processing techniques.

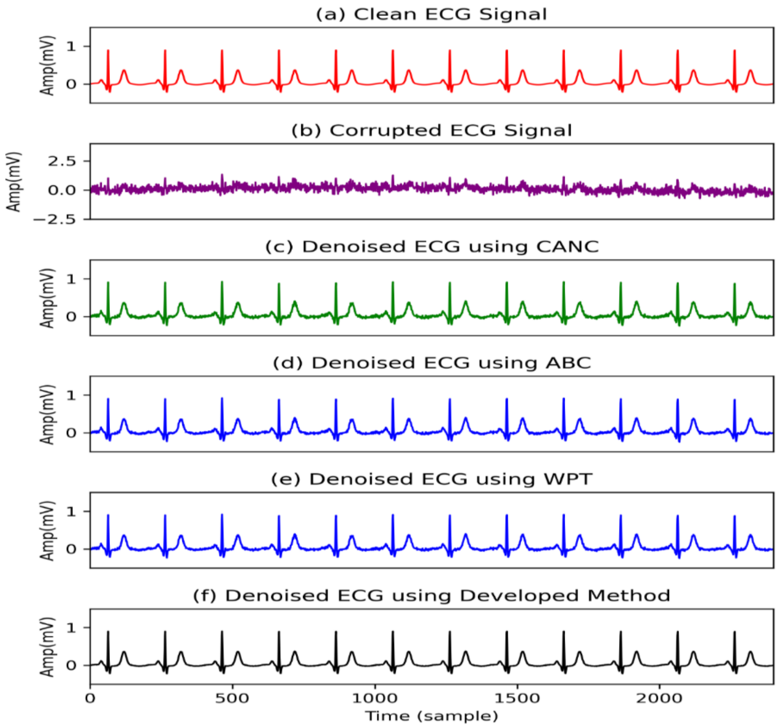

Figure 2a.

Performance of the Developed method validated against noise-corrupted NSRDB ECG record at -5dB (a) Clean NSRDB ECG record (b) Noise-corrupted NSRDB ECG record (c) Denoised ECG using CANC, (d) Denoised ECG using WPT, and (e) Denoised ECG using the developed method.

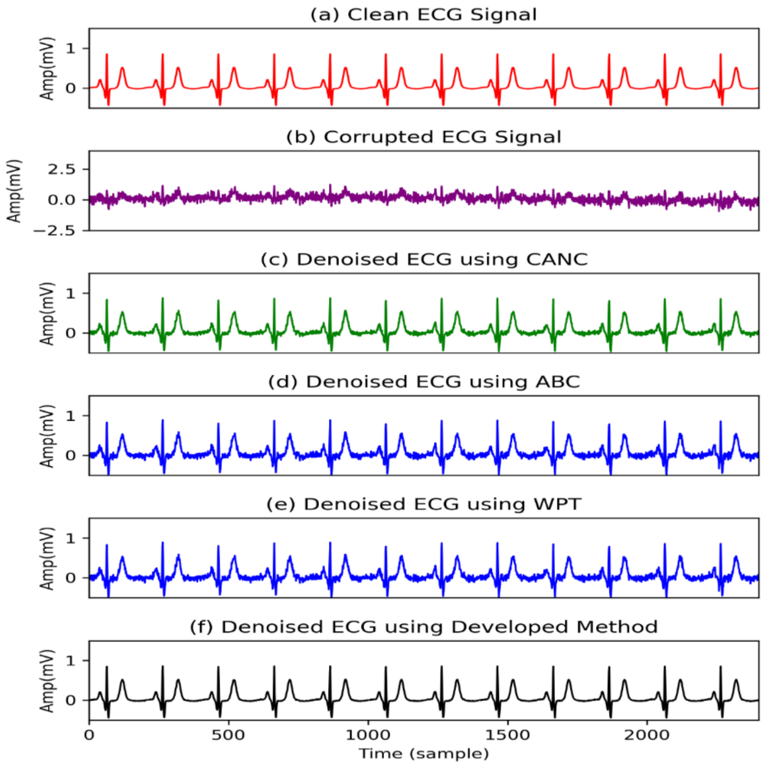

Figure 2b.

Performance of the Developed method validated against noise-corrupted MITDB ECG record at -5dB (a) Clean MITDB ECG record (b) Noise-corrupted MITDB ECG record (c) Denoised ECG using CANC, (d) Denoised ECG using WPT, and (e) Denoised ECG using the developed method.

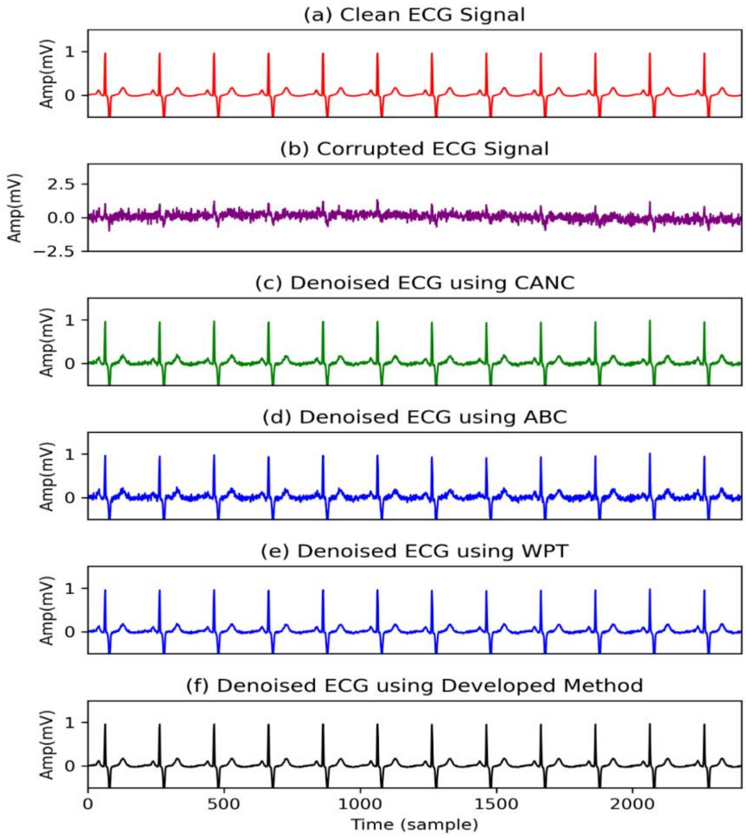

Figure 2c

Performance of the developed method validated against noise-corrupted QTDB ECG record at -5dB (a) Clean QTDB ECG record (b) Noise-corrupted QTDB ECG record (c) Denoised ECG using CANC, (d) Denoised ECG using WPT, and (e) Denoised ECG using the developed method

Discussion

Figure 2a displays a representative ECG waveforms obtained from the simulation tests, highlighting the qualitative differences in noise removal capabilities among the methods considered for the Normal Sinus Rhythm Database (NSRDB) ECG dataset. Visual examination of the results reveals significant differences in the quality of filtered ECG signals. The CANC method exhibited relatively moderate performance, successfully reducing high-frequency interference but struggling to preserve important diagnostic features such as the P-wave, T-wave, and especially the ST-segment. Conversely, the ABC-based method demonstrates improved performance, efficiently attenuating noise while generally maintaining crucial cardiac waveform features. The WPT method further improves waveform clarity, notably exhibiting better preservation of ECG morphology. However, the developed adaptive filter in this work showed an exceptional ability to eliminate noise across the entire frequency spectrum of interest, with minimal to no observable distortion of vital ECG features, thereby closely approximating the original, noise-free ECG signal.

At an input SNR of -5 dB, it is evident from the presented data that the proposed NLMS adaptive filter substantially outperforms all comparative methods.

Comparing the SNR output for each of the methods. The formula for obtaining the SNR output is given as:

$$SNR_{out}(dB) = 10log_{10}\left(\frac{\sum_{n=1}^{N}[x_{clean}(n)]^2}{\sum_{n=1}^{N}[x_{denoised}(n) - x_{clean}(n)]^2}\right)$$

Where;

- x_{clean} is the ground-truth clean ECG sample at index n.
- $x_{denoised}$ is the corresponding denoised ECG sample at index n.

A higher SNR_{out} indicates that the denoised signal is closer to the true clean ECG, meaning less residual noise and better preservation of the original waveform.

Performance Evaluation

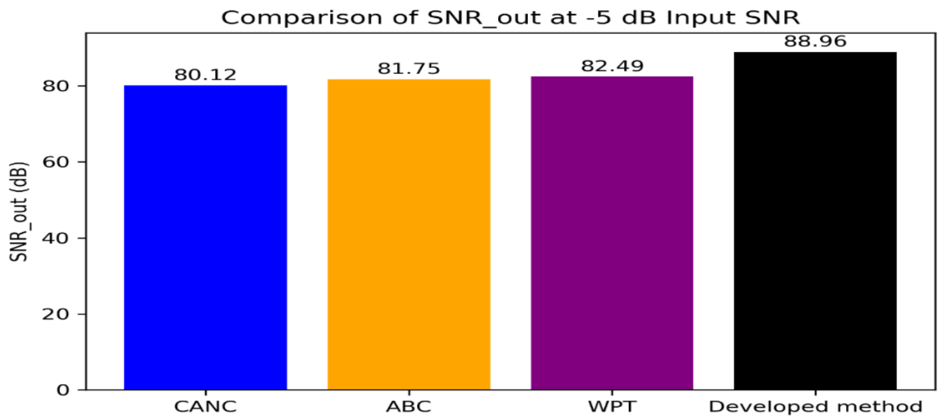

Figure 3a: Comparison of SNR output at -5 dB Input SNR

Specifically, as shown in figure 3a, for the severely contaminated ECG scenario (-5 dB), the proposed filter achieved a remarkable SNR_ output of 88.96 dB, significantly surpassing the results obtained by the best competing method (WPT), which yielded an SNR output of 82.49 dB

Correspondingly, as shown in 3b, the MSE achieved by the developed method is also low at 1.70×10^{-11}, a drastic improvement over the best alternative result (WPT, MSE = 9.51×10^{-7}). This represents a near-perfect noise removal, suggesting minimal signal distortion.

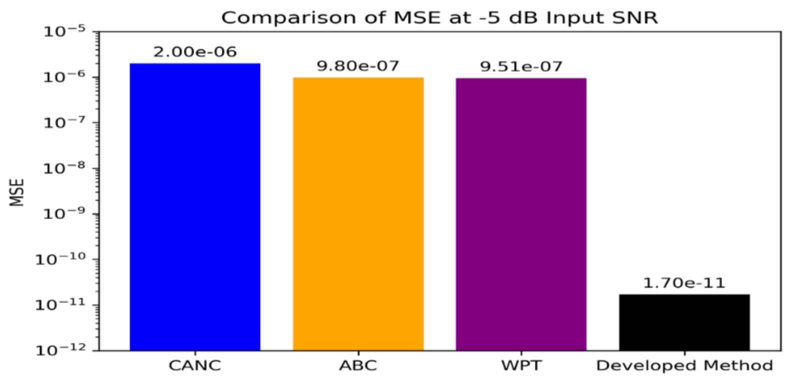

Figure 3b: Comparison of MSE at -5 dB Input SNR

In terms of maximum error (ME), mean difference (MD), and normalized RMSE (NRMSE), the developed adaptive filter also performed better. The ME and MD values recorded (2.65×10^{-5} and 6.53×10^{-9}, respectively) as shown in figure 3c are lower than those achieved by the compared methods. This improvement is critically important in clinical contexts, as lower values of ME and MD correspond directly to improved fidelity in clinical interpretations and diagnostics.

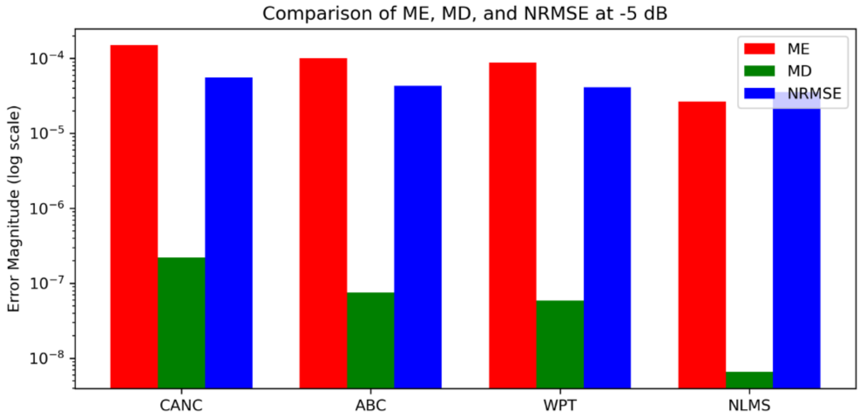

Figure 3c: Comparison of ME, MD, and NRMSE at -5 dB

Similar trends were observed across other input SNR scenarios (0 dB, 5 dB, and 10 dB). In each case, the developed adaptive filter consistently achieved superior results compared to CANC, ABC-based adaptive filter, as well as demonstrating notable performance advantages over the wavelet-based WPT method, widely regarded as highly effective in previous studies. This consistency across various noise levels and signal quality scenarios underscores the robustness and general applicability of the developed adaptive filtering approach.

Furthermore, correlation coefficient (CC) results shown in figure 3d consistently approached unity (1.0000) across all tested scenarios for the developed filter, clearly indicating that the filtered ECG signal produced by this method maintains an exceptionally high correlation with the original, clinically accurate ECG waveform. Such high CC values reinforce the practical significance of the developed method, particularly for critical medical diagnostic applications where the accurate preservation of ECG waveform morphology is paramount.

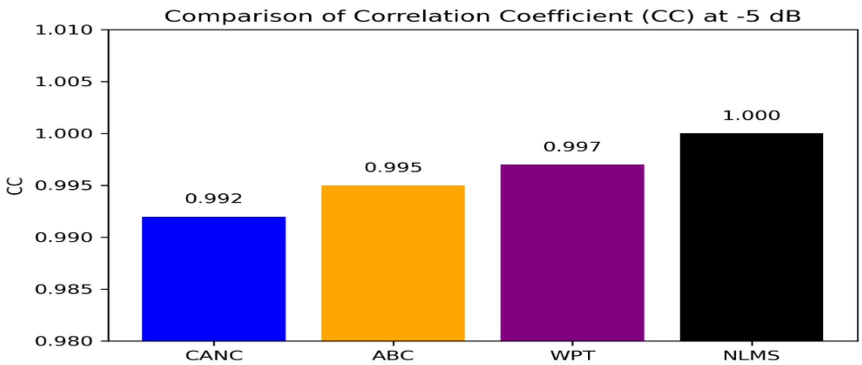

Figure 3d.

Finally, evaluating the output SNR values achieved by the developed adaptive filter at four different input SNR levels of $(-5\ dB,\ 0\ dB,\ 5\ dB, and\ 10\ dB)$. From the plot, it is observed that even in the worst case scenario of -5dB input SNR, the developed method achieved an output SNR of 88.96 dB, indicating substantial noise removal and signal preservation. As the input SNR improves toward 10 dB, the output SNR increased to 96.62dB, reflecting the filter's ability to retain the underlying ECG waveform with minimal residual noise. This performance trend highlights the robustness and general applicability of the proposed adaptive filtering approach across a range of noise conditions.

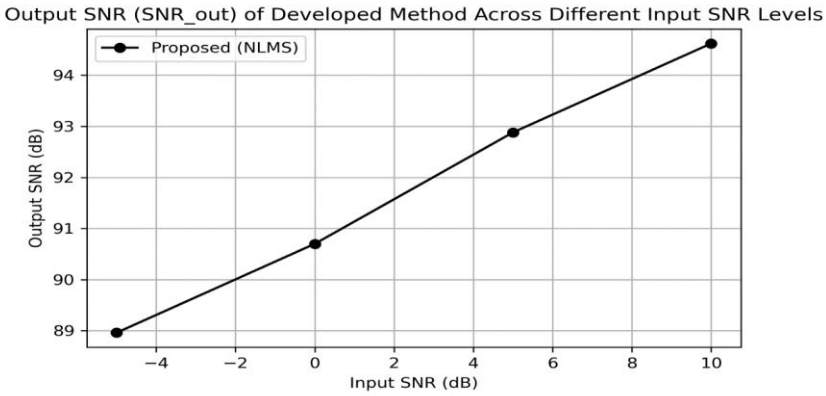

Figure 3e: Output SNR (SNR_out) of Developed Method Across Different Input SNR Levels

In summary, these comparative experimental results confirm that the developed adaptive filtering system did not only significantly enhances ECG noise suppression performance but also reliably preserves clinically significant ECG signal features.

Conclusion

The adaptive filtering technique, particularly when executed via the Normalized Least Mean Squares (NLMS) algorithm, consistently surpassed other methodologies identified in the literature, such as CANC, ABC, and wavelet-based techniques. The robust performance of the filter across different noise types, ECG datasets, and signal-to-noise ratio (SNR) levels suggests that the adaptive filtering approach has the potential for broader applicability in various clinical contexts and can be integrated into a diverse array of ECG monitoring systems.

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LINKS TO DATASET USED

1. MIT-BIH Arrhythmia Database (MITDB) : https://physionet.org/content/mitdb/1.0.0/
2. MIT-BIH Normal Sinus Rhythm Database (NSRDB): https://physionet.org/content/nsrdb/1.0.0/
3. MIT-BIH QT Database (QTDB): https://physionet.org/content/qtdb/1.0.0/

The CSV file for the data generated from the developed device is also available on request.