E-Health Telecommunication Systems and Networks, 2025, 14(3), 57-70
https://www.scirp.org/journal/etsn
ISSN Online: 2167-9525
ISSN Print: 2167-9517

Integrated Zero-Phase and LMS Adaptive Filtering for Improving Heartbeat Signal Processing

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How to cite this paper: Asker, A.M. and Okaf, A.M. (2025) Integrated Zero-Phase and LMS Adaptive Filtering for Improving Heartbeat Signal Processing. *E-Health Telecommunication Systems and Networks*, **14**, 57-70.
https://doi.org/10.4236/etsn.2025.143006

Received: September 1, 2025
Accepted: September 15, 2025
Published: September 18, 2025

Abstract

This paper presents a novel hybrid framework that integrates Zero-Phase filtering (ZP) with adaptive Least Mean Squares (LMS) filtering to enhance noise reduction in signal generation and processing applications. The study focuses on generating and improving human heart rate monitor signals by effectively reducing noise, particularly under nonstationary conditions, through the combined advantages of ZP filtering's distortion-free characteristics and the LMS algorithm's adaptive capabilities. The proposed approach first applies ZP filtering to maintain the signal's inherent features without introducing phase distortion, followed by adaptive LMS filtering to respond dynamically to varying noise conditions. Experimental tests on diverse non-stationary noise datasets reveal that this integrated method significantly outperforms individual filtering techniques in both noise suppression and signal fidelity. The findings demonstrate that the hybrid framework not only achieves superior noise reduction, closely simulating an electrocardiogram signal (ECG), but also preserves signal integrity, making it well-suited for world-time biomedical signal processing applications. This work introduces an innovative strategy that unites static and adaptive filtering techniques to address challenges posed by complex and random noise environments.

Keywords

Zero-Phase Filtering, LMS Adaptive Filtering, Noise Reduction

1. Introduction

Noise reduction plays a vital role in signal processing, as it directly impacts the quality and reliability of signals across various domains, including biomedical monitoring, communications, and audio processing. Effective noise suppression enhances signal clarity while preserving essential features, enabling accurate analysis and informed decision-making. Among the prevalent techniques, ZP filtering is favored for its capacity to eliminate noise without introducing phase distortion, thereby maintaining the signal's morphological integrity. However, ZP filtering is inherently static and lacks adaptability to non-stationary or time-varying noise environments. In contrast, adaptive LMS filtering dynamically adjusts filter coefficients to minimize the error between the desired and output signals. This adaptability allows world-time noise suppression in fluctuating environments, though it may introduce phase distortions and potential instability under certain conditions [1]. To leverage the strengths and mitigate the weaknesses of both methods, a hybrid filtering framework has been proposed. In this framework, ZP filtering serves as a pre-processing step that preserves signal phase and morphology, followed by LMS adaptive filtering, which continuously optimizes noise cancellation in response to changing noise characteristics. This combination enhances overall robustness, delivering superior noise reduction performance by uniting the stability of zero-phase filtering with the adaptability of LMS algorithms [2].

The study develops an integrated hybrid filtering framework by combining ZP filtering and adaptive LMS filtering for enhanced noise reduction in heart rate signal processing. The methodology proceeds in two main stages:

1) Zero-Phase Filtering: The initial step applies a zero-phase forward-backward filtering technique to the raw signal. This filter is designed to eliminate noise without introducing phase distortion, thereby preserving the temporal characteristics and morphological features of the heartbeat signal essential for accurate analysis [3].

2) Adaptive LMS Filtering: Following zero-phase filtering, an adaptive LMS filter is employed to further suppress residual noise. The LMS algorithm dynamically adjusts filter coefficients in real time based on the error signal, where its computational simplicity is the key advantage for choosing it among other filtering systems, which allows the framework to continuously adapt non-stationary noise environments typically encountered in physiological signal acquisition [4].

Signal datasets with various types of non-stationary noise are used to evaluate the proposed hybrid method. Performance metrics include noise reduction ratio, SNR improvement, and morphological fidelity of the filtered signals compared to ground truth or reference ECG signals. Comparisons against standalone ZP and LMS filtering validate the superior noise suppression and signal preservation capabilities of the integrated framework. Through this sequential filtering strategy, the methodology effectively unites the static precision of ZP filtering with the dynamic adaptability of LMS filtering, offering a robust solution for world-time biomedical signals affected by complex and unpredictable noise sources.

2. Methodology

As described in the referenced scientific paper [5]. Heart Rate Variability and Signal Components Heart Rate Variability (HRV) quantifies the variation in the intervals between heartbeats, known as RR intervals, reflecting autonomic nervous system modulation. The RR interval signal comprises two primary frequency components:

Low-frequency (*LF*) *component*: Occurs between 0.04 Hz and 0.15 Hz, representing a mixture of sympathetic and parasympathetic activity.

High-frequency (*HF*) *component*: Occurs between 0.15 Hz and 0.4 Hz and corresponds to respiratory sinus arrhythmia (RSA), which reflects parasympathetic (vagal) modulation linked to respiration [6].

Accurate separation of these components is essential for analyzing autonomic function. However, standard spectral analysis often causes power leakage between adjacent frequency bands, complicating this separation. Heart rate signals are acquired from single-lead ECG by extracting RR intervals using the (Pan and Tompkins QRS detection algorithm). The RR intervals are uniformly sampled at 50 Hz and down-sampled to 5 Hz for synchronization with respiratory signals measured as tidal volume ($V(t)$) via inductive plethysmography to prepare for filtering, the RR signals are de-trended using linear fitting, and a spectral density estimate is computed using (Welch's method), which averages multiple modified period grams with overlapping segments to reduce spectral leakage [7] [8].

2.1. Adaptive Filtering Framework

The integrated approach centers on an adaptive filter using the LMS algorithm to separate LF and HF components by modeling the relationship between the RR interval signal and the respiratory tidal volume signal.

- Filter Model: An FIR (Finite Impulse Response) filter of length N is used, where the filter coefficients are:

$$W = \left[w_0, w_1, \cdots, w_{N-1}\right] \tag{1}$$

which adapt to minimize the MSE between the predicted high-frequency component $y(k)$ and the actual observed RR interval $RR(k)$, where the filter output at discrete time k is given by:

$$y(k) = \sum_{i=0}^{N-1} w_i(k) V_t(k_i) \tag{2}$$

Here, $V_t(k)$ is the respiratory tidal volume reference signal at time k.

- Error Signal and Weight Update: The filter error $z(k)$, representing the low frequency component, is:

$$z(k) = RR(k) y(k) \tag{3}$$

The LMS algorithm updates the filter weights iteratively to minimize the expected squared error, using the gradient descent approach:

$$w_i(k+1) = w_i(k) + z(k) V_t(k_i) \tag{4}$$

- Adaptive Algorithm Characteristics: The weights are initialized to zero, at each sample, weights are updated based on instantaneous estimates without requiring prior knowledge of signal statistics. Over time, the weights converge to values that effectively predict the HF respiratory component within the RR signal. The output $z(k)$, representing the LF component, is obtained by subtracting the predicted HF component $y(k)$ from the total RR signal.

- Simulation and Mathematical Model of Signals: Simulated RR and tidal volume signals are constructed to emulate physiological conditions, facilitating filter testing. The RR interval signal s(t) mathematical forms are:

$$s(t) = C + A\sin\left(2\pi f_{h_t} + \alpha_h\right) + B\sin\left(2\pi f_{l_t} + \alpha_l\right) \tag{5}$$

Then tidal volume $V_t(k)$:

$$V_t(k) = D\sin\left(2\pi f_{h_t}\right) + E \tag{6}$$

where, A and B are the amplitudes of HF and LF components and C is the mean RR interval, while f_{h_t} and f_{l_t} are the high and low frequencies of respective components and α_h and α_l are the phases of HF and LF components, with D and E as amplitude and offset of tidal volume signal These signals are sampled with 1 ms resolution and then processed to a 5 Hz uniform sample rate for filtering [9].

2.2. Theoretical Outcome

This approach was developed to generate precise artificial heart rate variability (HRV) time series by mathematically modeling simplified physiological processes of the human body using MATLAB tools. It represents a significant advancement over existing methods that primarily replicate statistical features of recorded data but often overlook the underlying biophysical mechanisms governing heart rate variability, which many studies fail to address [10]. To prevent phase distortion artifacts common with filtering physiological signals, a zero-phase filtering technique is integrated with the adaptive filtering. The zero-phase filtering is achieved by:

- Filtering the input signal forward in time.
- Reversing the filtered signal in time and applying the same filter backward.

This two-pass filtering cancels phase distortion while maintaining the frequency response, thus preserving the shape and timing relationships in the heartbeat signal. Outcomes of the Mathematical Application:

1) The adaptive LMS filter successfully separates LF and HF components by using respiratory signal reference.

2) Zero-phase filtering ensures no phase shifts distort the filtered signals.

3) The algorithm converges over time, requiring tuning of filter length (typically $N = 20$) for optimal performance.

4) Simulated and real data analyses show improved spectral separation for cardiac autonomic control measurements.

This section synthesizes the core mathematical framework and adaptive filtering theory applied to heartbeat signal processing in the paper, detailing the LMS algorithm, signal models, zero-phase filtering, and their integration for physiological signal enhancement [11] [12]. Additionally, changing the seed of the random number generator produces different realizations of the random phases, ensuring that each new time series maintains the same temporal and spectral characteristics as the original data exactly as in **Figure 1** shown:

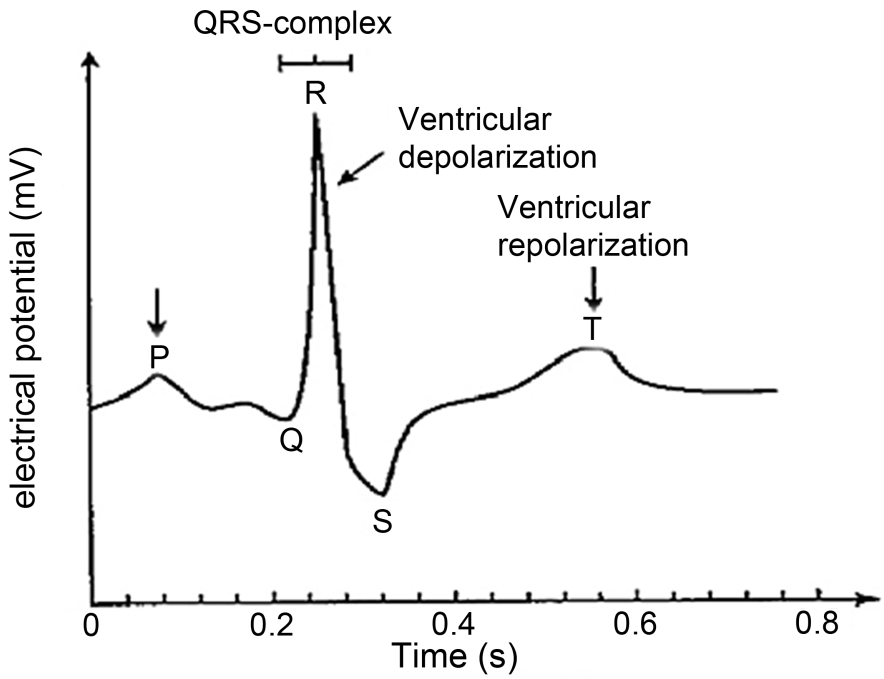

Figure 1. A single cycle of a typical ECG signal divided into P, Q, R, S, and T waves.

3. Proposed Hybrid Framework

ZP filtering is applied as a pre-processing step to eliminate phase distortions and maintain signal integrity by performing forward and backward filtering. This makes it particularly effective for handling stationary and repetitive noise. Following this, The adaptive LMS (Least Mean Squares) filter continuously updates its coefficients by minimizing the error between the filtered output and the desired signal because this process allows it to dynamically and effectively track and cancel out time-varying and non-stationary noise components. This adaptability happens as the filter measures the instantaneous error signal, which reflects how much the current output deviates from the desired clean signal, then adjusts the filter coefficients iteratively to reduce this error by following the gradient descent principle, hence minimizing the mean squared error .This continuous adaptation ensures that the filter coefficients are updated to reflect the changing noise characteristics, especially in environments where noise properties evolve rapidly over time.

The process essentially creates an estimate of the noise, which is subtracted from the noisy input to yield a cleaner output achieving a reduction factor of 0.6 [7]. This combined two-stage approach outperforms each technique individually, as evidenced by improvements in SNR, reduced MSE, and increased correlation with the clean reference signal [11]. Due to its computational efficiency, world-time adaptability, and phase-preserving properties, the framework is well-suited for applications in biomedical signal processing, communications, and other world-time systems facing dynamic noise conditions. By balancing stability and adaptability, this hybrid architecture offers a robust noise cancellation solution for complex environments, grounded in the established theories of adaptive LMS and ZP filtering documented in signal processing literature [13].

4. Description of Used Datasets

This approach leverages ZP filtering to remove fixed and repetitive noise components, ensuring no phase distortion in the wanted ECG signal, which is crucial for preserving signal morphology. Adaptive LMS filters complement this by dynamically adjusting filter parameters to suppress time-varying and non-stationary noise sources such as muscle artifacts, motion artifacts, and spectral interference [14]. To evaluate the framework's effectiveness, diverse datasets containing ECG signals corrupted by various noise types—including power line interference, baseline drift, EMG artifacts, and motion artifacts—are used to replicate realistic conditions [15]. These datasets allow assessment of ZP filtering's capability to handle steady-state noise and the adaptive LMS filters' ability to track and suppress dynamic noise. Consequently, the combination of ZP and adaptive LMS filters forms a robust hybrid system for world-time ECG signal enhancement across a wide range of challenging noise environments [16].

4.1. Noise Models and Simulation with Environmental Conditions

In this integrated framework, noise models and MATLAB simulations are designed to realistically replicate the distortions commonly encountered in various practical ECG acquisition scenarios, which include:

1) Power-line Interference (PLI): Spectral noise caused by electrical power systems, usually modeled as narrow-band sinusoidal interference at 50 or 60 Hz and harmonics.

2) Baseline Wander (BW): Low-frequency noise caused by respiration or body movements, modeled as slow varying trends or wandering baselines in the ECG waveform.

3) Electrocardiogram (EMG) Noise: Muscle activity noise with variable amplitude and frequency components, often modeled as band-limited stochastic or Gaussian noise to simulate muscle contractions contaminating the ECG.

4) Motion Artifacts: Noise introduced from patient movement or electrode cable motion, simulated as transient, irregular bursts or shifts, posing challenges due to their non-stationary, dynamic nature.

5) Electrode Contact Noise: Disturbances caused by electrode displacement or wearing, introduced as intermittent signal drops or spikes.

6) Simulation and Environmental Conditions: The data simulation uses short ECG segments (e.g., 10-second clips) often overlapping by 50 percent to avoid

information loss and abrupt transitions [17].

Different random noise types are superimposed on clean ECG signals under controlled or semi-supervised settings, replicating stable low-noise environments and highly dynamic, noisy environments respectively. Simulation models incorporate realistic noise amplitude and temporal characteristics to stress-test the adaptive LMS filter's ability to track and cancel non-stationary noise. Hybrid simulation environments combine multiple noise sources to test robustness across varied clinical and ambulatory conditions, where using these noise models and simulations enables realistic evaluation of the framework's effectiveness in improving the resulting ECG signal quality by increasing SNR and minimizing MSE, while preserving diagnostically important features in the ECG waveforms [18]. This type of noise modeling and environmental simulation reflects the requirements for practical world-time ECG monitoring systems to handle diverse noise challenges encountered in real-world conditions [19].

4.2. Performance Metrics for Evaluation

The primary performance metrics for evaluation focus on noise attenuation and signal fidelity, and most crucial of these metrics are:

- Signal-to-Noise Ratio (SNR): Measures the ratio of the power of the generated clean ECG signal to the power of the noise added. An increase in SNR after filtering indicates effective noise suppression and improved signal clarity.
- Mean Squared Error (MSE): Quantifies the average squared difference between the original clean signal and the filtered signal, where lower MSE values indicate better preservation of the original signal morphology with minimal distortion.
- Least Mean Squared Error (LMSE): The square root of MSE, providing a measure of the average magnitude of the error, and here it is useful for interpreting signal fidelity in the same units as the ECG amplitude [20] [21].

In various studies, combinations of these metrics show significant improvements in SNR (which often 30 - 60 percent), reduced MSE, and good percentage for correlation coefficients, demonstrating their effectiveness in realistic noisy conditions for reliable ECG monitoring and analysis. These metrics collectively ensure the framework not only removes the unwanted noise but also maintaining the diagnostic features of the ECG signal critical to be as downstream clinical interpretation and automated analysis [22].

5. Results and Discussion

5.1. Noise Reduction Performance

The integrated framework that combines ZP and adaptive LMS filters demonstrates strong noise reduction performance for enhancing ECG signals:

- Signal-to-Noise Ratio (SNR) Improvement: Studies show significant SNR improvements, with zero-phase filtering alone increasing SNR by around 5 dB, and adaptive LMS filters improving SNR by up to 10 dB or more.

- Mean Squared Error (MSE) Reduction: Adaptive LMS filters n this hybrid framework markedly reduce MSE compared to traditional filters, indicating better preservation of ECG morphology while attenuating noise.
- Correlation Coefficient (CC): Filtered signals frequently demonstrate high correlation coefficients with the ideal ECG signal, which is entirely free from distortion and noise, reflecting dependable signal accuracy. This bias has been utilized to demonstrate the degree to which the filtered signal is uncorrelated with the noisy input and how accurately correlated to the generated real signal [23].

5.2. Comparative Analysis Against Individual Zero-Phase

- ZP Filtering Alone: Primarily excels at removing fixed and repetitive noise such as baseline wander and power-line interference without introducing phase distortion, where effectively preserves the morphology of ECG signals due to its zero-phase characteristic. However, it struggles to suppress non-stationary, time-varying noise such as muscle artifacts (EMG) and motion artifacts that change dynamically in ambulatory or less controlled environments [24].
- Integrated Framework (ZP and Adaptive LMS Filters): Combines the strengths of zero-phase filtering for stationary noise with the adaptive LMS filter's capability to dynamically track and suppress time-varying and non-stationary noise sources. An added adaptive LMS filters outperform zero-phase filtering alone in improving SNR, particularly with noise types that vary quickly over time. Simulation results from studies show that adaptive LMS algorithms achieve higher SNR improvements (up to around 10-14 dB more) compared to ZP filtering alone. Adaptive filtering adapts filter coefficients in real-time based on signal error feedback, proving effective especially under changing noise conditions, while ZP filtering is fixed once designed [25].

5.3. Adaptability to Non-Stationary Noise

Adaptive LMS filters dynamically update their filter coefficients in real time based on the error between the noisy input and the desired signal, enabling the framework to effectively track and reduce time-varying noise components such as emotion artifacts, muscle (EMG) noise, and electrode interference (EI). While ZP filtering efficiently removes stationary and repetitive noise like power-line interference and baseline wander without phase distortion, where the adaptive LMS filter complements this by continuously adjusting to changing noise characteristics, resulting in superior overall noise suppression and signal fidelity in dynamic environments. Experimental results, including those from real-world ECG datasets, demonstrate that adaptive LMS filtering outperforms fixed filters in reducing noise metrics such as SNR and MSE under non-stationary conditions [26].

5.4. Noise Conditions

The Key points on noise reduction effectiveness across diverse noise scenarios include performance highlights under varying noise conditions:

- Stationary Noise (e.g., baseline wander, power-line interference): This stage in ZP filtering ensures baseline stability and eliminating a narrow-band interference, foundational for subsequent adaptive filtering performance.
- Non-Stationary Noise (e.g., motion artifacts, EMG noise): Adaptive LMS filters continuous adaptation capability offers superior noise cancellation even when noise characteristics change abruptly, typical in ambulatory or clinical environments.
- Composite Noise Scenarios: When both stationary and non-stationary noises coexist, the cascaded approach excels. Zero-phase filtering handles the stable noise first, then adaptive LMS filters refine the signal by removing residual and variable noise components with improved Signal-to-Noise Ratio (SNR) gains (often about 15 - 20 dB).
- Quantitative Metrics: Studies report that this integrated method yields significantly lower MSE and higher CC compared to standalone ZP filtering under these mixed noise conditions. Performance degradation is minimal even with increasing noise intensity or variation, indicating robustness [27].

This integrated framework demonstrates strong noise reduction capabilities, as clearly shown through a simulation that closely replicates real-world conditions using MATLAB. Figure 2 presents the ideal human heart rate function, which is then approximated by adding noise—illustrated in Figure 3—to create a more realistic simulation. The noisy signal is subsequently processed by the filters of the Hybrid System, shown in Figure 4, which is the main focus of our study.

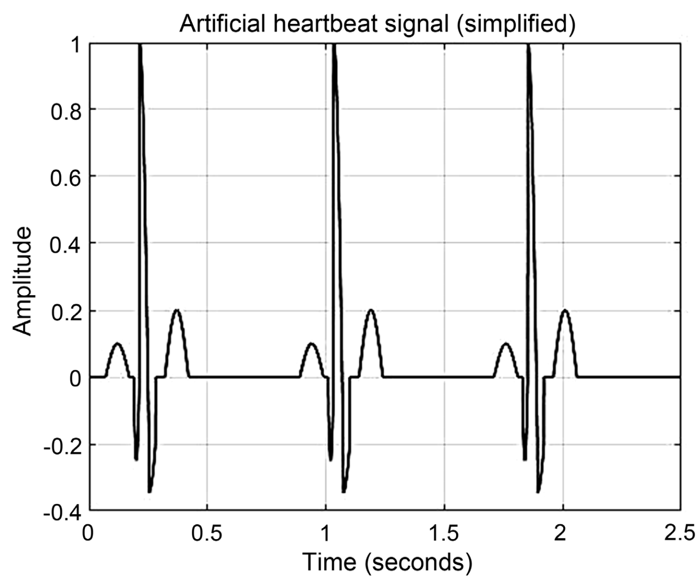

Figure 2. The ideal human heart rate generated signal.

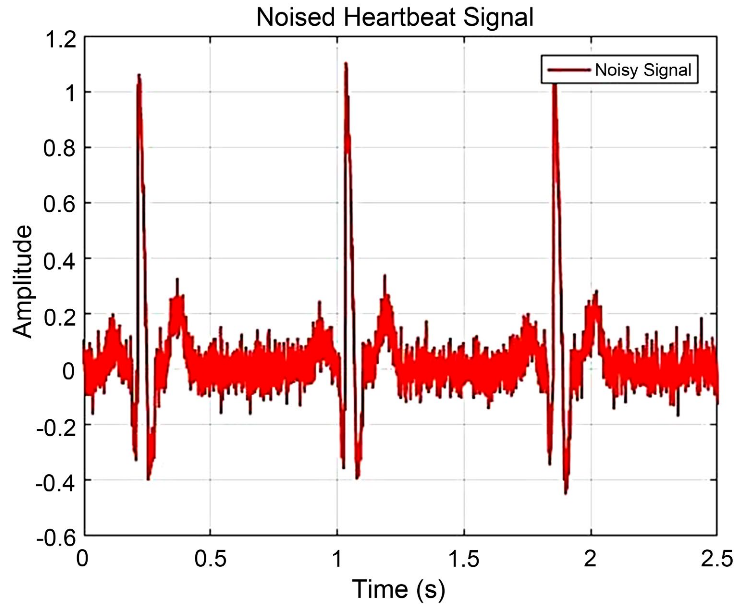

Figure 3. The noisy human heart rate generated signal.

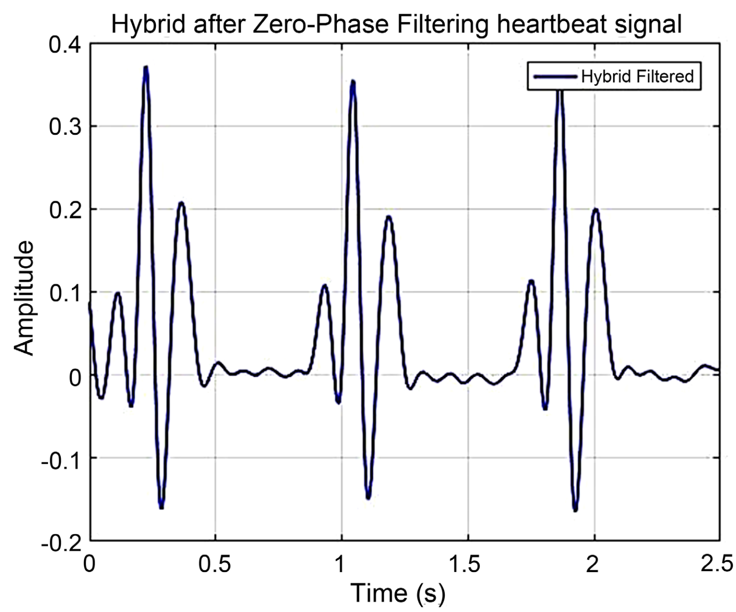

Figure 4. The filtered and most realistic human heart rate generated signal.

5.5. Communications System Noise Enhancement

The enhancement of noise performance in communication systems can be effectively evaluated using key signal quality metrics such as:

1) *Signal-to-Noise Ratio* (*SNR*): The Hybrid Filtering Framework aims to maximize SNR by minimizing noise components while preserving signal integrity. ZP filtering ensures no phase distortion, which is critical in the resulted signals, and LMS filtering adaptively suppresses time-varying noise.

2) *Mean Squared Error* (*MSE*): MSE serves as an objective measure of the filter's accuracy in noise reduction. The Hybrid scheme reduces MSE significantly com-

pared to standalone filtering techniques, indicating improved signal reconstruction and reduced distortion.

3) *Correlation Coefficient* (*CC*): Higher CC values indicate that the hybrid framework effectively retains the key features of the ideal signal while eliminating unwanted noise. This is essential for preserving the similarity between the desired and resulting signals, ensuring a more accurate determination of the convergence ratio [24] [25]. **Table 1** presents a comparison between the noisy signal and the signal filtered through the hybrid filtering system, accompanied by an illustration of this relationship in the corresponding **Figure 5**.

Table 1. The comparisons of results.

SNR (dB)	Mean Squared Error	
	Noisy Signal	**Filtered Signal**
−0.28933	0.0083908	0.0032902
0.42629	0.0069507	0.0027777
2.22	0.0045406	0.0019728
3.2177	0.0035968	0.0019172
4.5294	0.0025373	0.0016758
Least Square Mean Error:		
Noisy: 0.0052032 Filtered: 0.0023267		

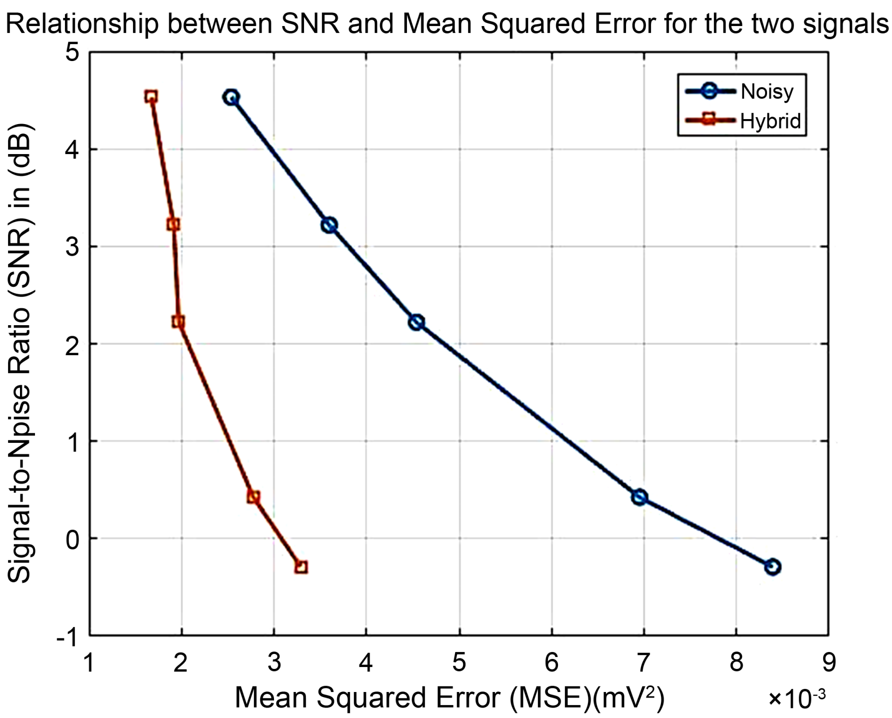

Figure 5. Relationship between SNR and MSE for the two signals.

6. Conclusion and Future Works

Key results indicate that the ZP filter prevents phase distortion, maintaining signal integrity, whereas the LMS adaptive filter adjusts dynamically to a fast time varying noise, reducing the mean square error and improving the signal-to-noise ratio. This combined method offers the benefits of both stability and adaptability, surpassing traditional single-filter techniques in managing both stationary and non-stationary noise environments. The hybrid framework's ability to sustain a strong correlation with the ideal signal while minimizing divergence highlights its robustness, and its potential impact on world-time signal processing is significant, delivering improved performance in applications that demand accurate, distortion-free signals amid fluctuating noise, such as biomedical monitoring and acoustic systems, thereby enabling more reliable and efficient real-time noise cancellation solutions. Future works for such an integrated hybrid framework could focus on several promising directions. First, enhancing the computational efficiency and convergence speed of the LMS adaptive filter to enable deployment in low-power, real-time embedded systems is crucial. Second, extending the framework to incorporate advanced adaptive filtering algorithms such as Recursive Least Squares (RLS) or nonlinear adaptive filters could improve noise cancellation performance in more complex and non-stationary noise environments. Third, integrating machine learning techniques for dynamic parameter tuning and adaptive thresholding may offer improved robustness against diverse noise sources. Moreover, extending the application of the hybrid framework to a broader variety of biomedical signals, which not limited to ECG only, could facilitate its validation and enhance its practical usefulness. Finally, experimental validation using large-scale, real-world datasets with varying noise characteristics would strengthen the framework's reliability and pave the way for commercial implementations in medical devices and audio systems.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Oppenheim, A.V. and Schafer, R.W. (2010) Discrete-Time Signal Processing. 3rd Edition, Pearson.

[2] Haykin, S. (2002) Adaptive Filter Theory. 4th Edition, Prentice Hall.

[3] DSP System Toolbox (2024). Release Highlights—MATLAB and Simulink. https://www.mathworks.com/help/dsp/index.html

[4] Ang, W.T., Krichane, M. and Sim, T. (2006) Zero Phase Filtering for Active Compensation of Periodic Physiological Motion. *The First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics*, 2006. *BioRob* 2006, Pisa, 20-22 February 2006, 182-187. https://doi.org/10.1109/biorob.2006.1639081

[5] Farhang-Boroujeni, B. (2013) Adaptive Filters: Theory and Applications. 2nd Edition, John Wiley and Sons, Ltd.

[6] Keenan, D. and Grossman, P. (2006) Adaptive Filtering of Heart Rate Signals for an

Improved Measure of Cardiac Autonomic Control. *International Journal of Signal Processing*, **2**, 52-58.

[7] An, X. and K. Stylios, G. (2020) Comparison of Motion Artefact Reduction Methods and the Implementation of Adaptive Motion Artefact Reduction in Wearable Electrocardiogram Monitoring. *Sensors*, **20**, Article 1468. https://doi.org/10.3390/s20051468

[8] von Rosenberg, W., Hoting, M. and Mandic, D.P. (2019) A Physiology Based Model of Heart Rate Variability. *Biomedical Engineering Letters*, **9**, 425-434. https://doi.org/10.1007/s13534-019-00124-w

[9] Hermont, I.K.D.S., Flores, A.R. and De Lamare, R.C. (2025) Robust Adaptive Filtering with the Hyperbolic Tangent Exponential Kernel M-Estimator Function for Active Noise Control. *IEEE Access*, **13**, 148522-148532. https://doi.org/10.1109/access.2025.3601570

[10] Dotsinsky, I. (2007) Review of "Advanced Methods and Tools for ECG Data Analysis", by Gari D. Clifford, Francisco Azuaje and Patrick E. Mcsharry (Editors). *BioMedical Engineering OnLine*, **6**, Article No. 18. https://doi.org/10.1186/1475-925x-6-18

[11] McSharry, P.E., Clifford, G.D., Tarassenko, L. and Smith, L.A. (2003) A Dynamical Model for Generating Synthetic Electrocardiogram Signals. *IEEE Transactions on Biomedical Engineering*, **50**, 289-294. https://doi.org/10.1109/tbme.2003.808805

[12] Almasi, A., Shamsollahi, M.B. and Senhadji, L. (2011) A Dynamical Model for Generating Synthetic Phonocardiogram Signals. 2011 *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, 30 August 2011-3 September 2011, 5686-5689. https://doi.org/10.1109/iembs.2011.6091376

[13] McSharry, P.E., Clifford, G., Tarassenko, L. and Smith, L.A. (2002) Method for Generating an Artificial RR Tachogram of a Typical Healthy Human over 24-Hours. *Computers in Cardiology*, Memphis, 22-25 September 2002, 225-228. https://doi.org/10.1109/cic.2002.1166748

[14] Rehman, S.A., Kumar, R. and Rao, M. (2012) Performance Comparison of Various Adaptive Filter Algorithms for ECG Signal Enhancement and Baseline Wander Removal. 2012 *Third International Conference on Computing*, *Communication and Networking Technologies* (*ICCCNT*'12), Coimbatore, 26-28 July 2012, 1-5. https://doi.org/10.1109/icccnt.2012.6396032

[15] Menaceur, N.E., Kouah, S. and Derdour, M. (2024) Adaptive Filtering Strategies for ECG Signal Enhancement: A Comparative Study. 2024 6*th International Conference on Pattern Analysis and Intelligent Systems* (*PAIS*), El Oued, 24-25 April 2024, 1-6. https://doi.org/10.1109/pais62114.2024.10541144

[16] Balasubramanian, S. and Naruka, M.S. (2022) A Noise Removal Methodology for Effective ECG Enhancement in Heart Disease Prediction & Analysis. *International journal of health sciences*, **6**, 11578-11593. https://doi.org/10.53730/ijhs.v6ns1.7813

[17] Keshavamurthy, T.G. and Eshwarappa, M.N. (2019) ECG Signal De-Noising Based on Adaptive Filters. *International Journal of Innovative Technology and Exploring Engineering*, **9**, 5473-5483. https://doi.org/10.35940/ijitee.K1601.119119

[18] Hu, H. (2024) Simulation Analysis of ECG Denoising Based on Common Mode Feedback Technology. *Highlights in Science*, *Engineering and Technology*, **111**, 69-75. https://doi.org/10.54097/xafxbc59

[19] Kaur, P. (2024) Review on Filtering Strategies for Enhanced ECG Signal Quality. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Hyderabad, 7-9 November 2024, 299-308.

https://doi.org/10.46254/in04.20240090

[20] Al-Qazzaz, N.K., Buniya, A., A. Aldoori, A., Mohd Ali, S.H. and Ahmad, S.A. (2024) Noise Modeling and Removal from Electrocardiogram Signals: A Study Using Wavelet Transform with Graphical User Interface. *International Journal of Integrated Engineering*, **16**, 26-36. https://doi.org/10.30880/ijie.2024.16.07.003

[21] Iqbal, M.A. and Quaff, A.R. (2024) Oxide Based Composite for Selective Separation of Oxygen from the Atmospheric Air. https://nano-ntp.com/index.php/nano/article/view/1812

[22] Mathworks (2024) Zero-Phase Filtering. https://www.mathworks.com/help/signal/ref/zerophase.html

[23] Waheed, M. (2023) Pre-Processing of ECG Signal Based on Multistage Filters. *Journal of Integrated Circuits and Systems*, **18**, 1-6. https://doi.org/10.29292/jics.v18i2.698

[24] Prashar, N. and Sood, M. (2022) Design and Performance Analysis of Cascade Digital Filter for ECG Signal Processing. *International Journal of Innovative Technology and Exploring Engineering*, **8**, 2659-2665.

[25] Sharma, N. and Singh Sidhu, J. (2016) Removal of Noise from ECG Signal Using Adaptive Filtering. *Indian Journal of Science and Technology*, **9**, 1-6. https://doi.org/10.17485/ijst/2016/v9i48/106424

[26] An, X. and K. Stylios, G. (2020) Comparison of Motion Artefact Reduction Methods and the Implementation of Adaptive Motion Artefact Reduction in Wearable Electrocardiogram Monitoring. *Sensors*, **20**, Article 1468. https://doi.org/10.3390/s20051468

[27] Lampl, T. (2020) Implementation of Adaptive Filtering Algorithms for Noise Cancellation. https://www.diva-portal.org/smash/get/diva2:1456739/FULLTEXT01.pdf