RESEARCH PAPER

Enhanced ECG Signal Processing Through GA-Optimized SD-LMS Adaptive Filtering

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Abstract

This study introduces a novel adaptive filtering technique to effectively reduce noise in electrocardiogram (ECG) signals by leveraging a Genetic Algorithm (GA)-tuned Signed Data-Least Mean Square (SD-LMS) algorithm. ECG signals are essential in the diagnosis and monitoring of cardiovascular conditions, including arrhythmias, ischemic events, and other heart abnormalities. However, their accuracy is often compromised by noise sources, primarily baseline wander (BLW) and power line interference (PLI), which can obscure critical features such as the P, QRS, and T waveforms that are crucial for clinical interpretation. BLW, a low-frequency noise, is commonly introduced by patient movement and respiration, while PLI, a high-frequency interference often at 50 or 60 Hz, originates from nearby electrical devices or improper grounding. These noises complicate ECG analysis and can lead to misinterpretation or missed diagnoses if not adequately filtered.

Existing noise removal techniques, while useful, often lack adaptability and can be computationally demanding, making them unsuitable for real-time applications in embedded systems and portable medical devices. Adaptive filters, such as those in the Least Mean Square (LMS) algorithm family, are widely regarded for their ability to dynamically adjust filter parameters in response to noise changes. The SD-LMS variant, in particular, is computationally efficient, making it well-suited for resource-limited applications. However, a limitation of LMS-based filters is that their performance depends on the step size parameter (μ), which governs the speed and accuracy of convergence. An inappropriate step size can lead to slow convergence or even filter divergence, negatively impacting the quality of noise reduction.

To address this limitation, the proposed method uses a Genetic Algorithm (GA) to optimize the step size of the SD-LMS filter. GAs are heuristic optimization techniques inspired by natural selection and are effective for complex search and optimization tasks. In this approach, the GA iteratively tunes the step size based on its ability to maximize the Signal-to-Noise Ratio (SNR), resulting in a filter that adapts efficiently to noise without requiring manual parameter adjustments. This optimization process enables the GA-tuned SD-LMS filter to achieve robust noise reduction across various noise profiles.

The proposed filtering method was validated using records from the MIT-BIH Arrhythmia and Noise Stress Test databases, which are standard datasets in biomedical research. The GA-tuned SD-LMS filter demonstrated an average SNR improvement of 10.754 dB for BLW and 24.08 dB for PLI, significantly surpassing traditional filtering techniques. Moreover, the high correlation coefficients achieved indicate that this filter preserves essential ECG features, enhancing the reliability of ECG signal analysis in clinical and real-time monitoring applications. This adaptive filtering approach shows promise for integration into wearable ECG devices, where maintaining signal fidelity in noisy environments is critical for patient care.

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1. Introduction

Electrocardiography (ECG) is a critical tool in cardiac diagnostics, widely used to monitor and evaluate heart health. Through ECG recordings, clinicians can detect and diagnose a variety of heart conditions, including arrhythmias, ischemic episodes, and other cardiovascular disorders. Accurate ECG readings are essential, as the signal provides vital information about the heart's electrical activity and rhythm. However, ECG signals are often compromised by noise, making interpretation challenging and potentially leading to inaccurate diagnoses if the noise is not effectively filtered out. Two predominant types of noise in ECG recordings are baseline wander (BLW) and power line interference (PLI), both of which can significantly distort the signal and reduce diagnostic precision (Goldberger et al., 2000).

Baseline wander (BLW) is a low-frequency noise caused primarily by factors such as patient movement, respiratory cycles, and changes in electrode position. This noise appears as a drifting baseline in the ECG, which can obscure the P, QRS, and T waveforms—key features that indicate cardiac cycles. Power line interference (PLI), on the other hand, is a high-frequency noise often introduced by surrounding electrical devices or improper grounding of the ECG equipment. PLI typically appears at 50 or 60 Hz and can interfere with the clarity of the ECG signal, complicating analysis. Together, these noise types can make it difficult to identify crucial ECG features accurately, underscoring the need for effective noise removal methods in real-time monitoring applications.

Adaptive filters have become popular for ECG noise reduction because of their ability to dynamically adjust to the changing noise characteristics in ECG signals. The Least Mean Square (LMS) family of algorithms is particularly effective in adaptive filtering, as it adjusts filter parameters to minimize the error between the signal and a reference noise source. However, conventional LMS filters have limitations in terms of computational efficiency and require careful tuning of the step size parameter (μ). An improperly set step size can result in slow convergence or even cause the filter to diverge, reducing its effectiveness in real-time applications. The Signed Data-LMS (SD-LMS) variant is a computationally efficient version of LMS, designed for resource-limited environments, making it suitable for portable ECG monitoring devices.

This study proposes a Genetic Algorithm (GA)-tuned SD-LMS filter to address these limitations. Unlike traditional filters, this approach uses a GA to automatically optimize the step size parameter, enhancing the filter's adaptability and performance. Genetic Algorithms (GAs) are inspired by natural selection and are widely used for complex optimization problems. In this application, the GA iteratively adjusts the step size based on the filter's Signal-to-Noise Ratio (SNR) improvement, selecting the best-performing parameters through evolutionary operations like selection, crossover, and mutation. This approach ensures optimal noise suppression without requiring manual tuning, allowing the filter to adapt efficiently to diverse noise profiles.

The GA-tuned SD-LMS filter was tested on ECG records from the MIT-BIH Arrhythmia and Noise Stress Test databases, demonstrating significant noise reduction and superior signal integrity compared to conventional filtering methods. This optimized filter achieved high SNR values for both BLW and PLI, making it a promising solution for real-time ECG monitoring in clinical and wearable devices, where both signal fidelity and computational efficiency are critical.

2. Materials and Methods

2.1 ECG Databases

Data for this study was sourced from PhysioNet, a comprehensive open-access resource for biomedical signals and related tools (Goldberger et al., 2000; Goldberger et al., 2015). PhysioNet has been instrumental in advancing research by providing access to well-documented datasets and algorithms for signal analysis, making it a cornerstone for biomedical engineering and clinical applications. Among its repositories, the PhysioBank database is particularly noteworthy, as it hosts a variety of physiologic signal recordings, including ECG data, which are widely used in cardiac studies. For this research, two specific databases from PhysioBank were selected to validate the proposed GA-tuned SD-LMS algorithm: the MIT-BIH Noise Stress Test Database and the MIT-BIH Arrhythmia Database. These datasets were chosen because they provide complementary challenges in ECG signal processing.

The MIT-BIH Noise Stress Test Database was specifically designed to simulate real-world noise conditions that commonly occur in clinical ECG recordings. It includes 12 half-hour ECG recordings with superimposed noise artefacts, as well as three half-hour recordings containing isolated noise signals such as baseline wander (BLW), muscle artefacts, and power line interference (PLI). This dataset is ideal for evaluating noise removal techniques because it provides a controlled environment where the performance of filtering algorithms can be tested against known noise profiles. In this study, the BLW signals from this database were used to simulate low-frequency baseline shifts, while an artificially generated 60 Hz sinusoidal signal was used to represent PLI. These noise components are representative of the challenges faced in real-time ECG monitoring, where maintaining signal fidelity is critical for accurate diagnosis.

The MIT-BIH Arrhythmia Database, on the other hand, is a benchmark dataset for evaluating the effectiveness of noise removal in preserving clinically relevant features (Moody & Mark, 2001). This database contains 48 half-hour recordings of ECG signals sourced from 47 individuals, with annotations for various arrhythmic events. The recordings include a diverse range of heart rhythm patterns, including complex ventricular, junctional, and supraventricular arrhythmias, as well as conduction abnormalities. Approximately 60% of the recordings were obtained from inpatients, ensuring that the dataset captures a wide spectrum of cardiac conditions. The arrhythmic annotations were meticulously reviewed by cardiologists, making this dataset invaluable for assessing how well a filtering method preserves diagnostically significant ECG features.

The combination of these two databases allows for a comprehensive evaluation of the GA-tuned SD-LMS algorithm. The Noise Stress Test Database provides a rigorous framework for testing noise suppression capabilities, while the Arrhythmia Database ensures that the filtered ECG signals retain their diagnostic integrity. By leveraging these datasets, this study demonstrates the robustness and clinical relevance of the proposed filtering technique in diverse noise scenarios.

2.2 Noise Sources in ECG Signals

Noise in ECG signals comes from various sources that can obscure the essential waveforms required for accurate cardiac diagnosis. The primary noise sources impacting ECG recordings include baseline wander (BLW), power line interference (PLI), and muscle artefacts or electrode noise. Each of these noise types has unique characteristics that make effective filtering challenging and highlight the need for adaptable, efficient noise-removal techniques.

Baseline Wander (BLW): BLW is a low-frequency noise generally caused by slow changes in the baseline of the ECG waveform. This noise is primarily introduced by patient movements, respiration cycles, or shifts in electrode placement, leading to a drifting baseline that can obscure important ECG features like the P, QRS, and T waves. BLW typically occurs in the 0.05 to 0.5 Hz range, making it challenging to distinguish from low-frequency components of the ECG signal itself. If not effectively removed, BLW can interfere with automated ECG analysis and obscure diagnostic information, as it can shift the entire ECG waveform up or down, complicating the accurate measurement of intervals and amplitudes. Filtering out BLW requires a technique that can accurately separate the slow-varying noise from the true baseline of the ECG.

Power Line Interference (PLI): PLI is a high-frequency noise typically caused by alternating current (AC) power sources near the ECG recording equipment. It appears as a periodic interference at the AC frequency of the local power grid, usually 50 Hz or 60 Hz, and can have significant amplitude, depending on factors such as equipment grounding and proximity to electrical devices. PLI can create a constant oscillatory disturbance across the ECG waveform, making it difficult to identify finer details of the signal. Unlike BLW, PLI is a higher-frequency noise and thus requires a different filtering approach to avoid interfering with ECG components in the higher frequency ranges. Effective PLI removal is crucial for ensuring that the QRS complexes and other rapid changes in the ECG are not masked by this type of noise, which could impair the accuracy of diagnostics, particularly in rhythm analysis and real-time monitoring (Sun et al., 2002).

Muscle Artefacts and Electrode Noise: These noise types are typically irregular, high-frequency interferences that result from muscle contractions, movement, and variations in skin-electrode contact. Muscle artefacts occur when voluntary or involuntary muscle activity produces electrical signals that overlap with the ECG waveform, typically manifesting as bursts of high-frequency noise. Similarly, electrode noise results from fluctuating contact quality between the skin and the electrode, often due to slight movements or perspiration, creating transient disturbances in the ECG signal. Muscle artefacts and electrode noise can obscure crucial parts of the ECG waveform, such as the QRS complex, and add complexity to signal processing. Since these noises are non-stationary and can occur at various frequencies, they are particularly challenging to filter, requiring adaptive filtering techniques that can adjust in real-time.

These noise sources introduce significant challenges in ECG signal processing, as each requires a different approach to isolate and filter out effectively. Traditional filtering techniques can sometimes distort or remove parts of the ECG signal itself, especially when noise frequencies overlap with those of the signal. Thus, advanced adaptive filtering algorithms, such as the GA-tuned SD-LMS algorithm used in this study, are essential for dynamically adjusting to various noise profiles, thereby preserving the integrity of the ECG signal and supporting more accurate diagnostic assessments (Rangayyan, 2004).

2.3 Adaptive Filtering Algorithms

Adaptive filtering algorithms play a crucial role in dynamic signal processing environments where system characteristics are unknown or time-varying. Among these, the Least Mean Squares (LMS) algorithm family is widely adopted due to its simplicity, robustness, and ease of implementation (Rahman et al., 2009; Hao et al., 2011). The LMS algorithm operates on the principle of minimizing the mean square error (MSE) between a desired signal and the filter output by iteratively updating the filter coefficients in the negative gradient direction of the error surface. This gradient-descent approach allows the filter to automatically track changes in signal statistics, making it suitable for non-stationary environments such as biomedical signal processing, noise cancellation, and communication systems.

However, the performance of the conventional LMS algorithm strongly depends on the appropriate selection of the step size parameter. A large step size leads to faster convergence but may cause instability and higher steady-state error, whereas a small step size ensures stability at the expense of slower convergence. To address this trade-off, variants such as the Sign-Data LMS (SD-LMS) algorithm have been developed. The SD-LMS reduces computational complexity by using the sign of the input signal during weight adaptation, significantly lowering multiplication requirements. This makes it particularly suitable for real-time and embedded hardware implementations where processing power and memory are limited.

Furthermore, optimization techniques such as Genetic Algorithms (GA) can be employed to dynamically tune the step size parameter. GA-based optimization enhances convergence speed and stability by adaptively selecting optimal learning parameters, thereby improving overall filter performance in rapidly changing signal environments.

2.4 Proposed GA-Tuned SD-LMS Filtering Method

Genetic Algorithms (GAs) play a crucial role in optimizing the Signed Data-Least Mean Square (SD-LMS) filter by dynamically tuning the step size (μ) to maximize Signal-to-Noise Ratio (SNR) and enhance the overall filtering performance. GAs are heuristic optimization techniques inspired by the principles of natural selection and evolution. They are particularly well-suited for complex, non-linear optimization problems where traditional approaches may struggle to find optimal solutions efficiently. In the context of ECG signal filtering, GAs provide a powerful means to iteratively search for the optimal step size, which directly influences the convergence speed and accuracy of the SD-LMS filter.

The optimization process begins by initializing a population of candidate step size values, each representing a potential solution. The GA algorithm then iteratively refines this population to find the best step size (μ) that maximizes the SNR while ensuring the filter converges efficiently and accurately. The GA optimization process involves several key steps, including selection, crossover, and mutation, which are designed to emulate the process of natural selection. These steps are described in detail below:

Selection: In the selection phase, the GA evaluates each candidate solution's fitness, which, in this case, is determined by the SNR improvement achieved with each step size value. The higher the SNR, the more effective the step size is at minimizing noise without distorting the ECG signal. The best-performing candidates—those that yield the highest SNR values—are selected to pass on their "genetic material" (step size information) to the next generation. By selecting the top-performing candidates, the GA ensures that only the most promising solutions are retained for further refinement, focusing computational resources on the most effective parameters.

Crossover: Crossover is a process that mimics genetic recombination, where selected parent candidates are combined to create new offspring solutions. In this context, crossover allows the GA to explore new step size values by blending the characteristics of two high-performing solutions. This process creates variation in the population and can lead to better-performing step sizes in the offspring. Crossover helps the GA avoid getting stuck in local optima by introducing new combinations that may yield higher SNR values, thus improving the overall performance of the SD-LMS filter.

Mutation: Mutation introduces random variations to some candidates, altering their step size values to explore a broader range of possible solutions. This step prevents the algorithm from converging too quickly to a suboptimal solution, providing a mechanism to escape local maxima or minima in the optimization landscape. By randomly adjusting step sizes, mutation helps maintain diversity within the population, which is essential for achieving a robust global optimization. Mutation is typically applied at a low rate to maintain stability in the population while still encouraging exploration.

This GA-tuned approach to step size selection provides a significant advantage over traditional methods, where step size is often set manually and may not be optimized for different noise conditions. By using GAs to continuously optimize μ, the SD-LMS filter can dynamically adapt to various noise profiles without requiring manual adjustments. This adaptability is particularly beneficial for ECG filtering, as noise characteristics in ECG signals can vary widely between patients and recording environments.

In this study, the GA-tuned SD-LMS filter configuration was implemented in MATLAB, with a filter length of 5 selected for computational efficiency and effectiveness in noise suppression. The GA parameters—such as population size, crossover rate, and mutation rate—were carefully optimized to ensure fast convergence and reliable real-time performance. By leveraging the strengths of GAs in adaptive filtering, this configuration allows the SD-LMS filter to maximize SNR, providing a highly effective noise-removal solution suitable for real-time ECG monitoring applications.

3. Results

3.1 ECG Noise Removal with Baseline Wander (BLW)

The experimental evaluation demonstrates that the GA-optimized SD-LMS algorithm significantly enhances ECG signal quality in the presence of baseline wander noise. Baseline wander, typically caused by respiration, patient movement, and electrode impedance variations, introduces low-frequency distortions that obscure critical ECG components such as the P-wave, QRS complex, and T-wave. Effective removal of this artefact is essential for accurate diagnosis and automated feature extraction.

As shown in Table 1, all selected records from the MIT-BIH Arrhythmia Database exhibited substantial SNR improvements after filtering. The average SNR increased from 2.108 dB to 12.862 dB, yielding a mean improvement of 10.754 dB. Notably, record 108 achieved the highest improvement of 14.27 dB, indicating strong adaptability of the algorithm to severe noise conditions. Additionally, the consistently high correlation coefficients (average 0.974) confirm that the denoising process preserved the morphological integrity of the ECG waveforms. This balance between noise suppression and waveform preservation highlights the robustness and clinical reliability of the GA-tuned SD-LMS approach for real-time ECG signal enhancement.

Table 1: SNR Improvement and Correlation Coefficient for BLW

Record	**SNR before (dB)**	**SNR after (dB)**	**Improvement (dB)**	**Correlation Coefficient**
100	0.82	11.26	10.44	0.97
105	3.67	13.55	9.88	0.98
108	1.14	15.41	14.27	0.98
203	2.54	11.21	8.67	0.98
228	2.37	12.88	10.51	0.96
Avg	**2.108**	**12.862**	**10.754**	**0.974**

3.2 ECG Noise Removal with Power Line Interference (PLI)

The performance of the GA-optimized SD-LMS algorithm was further evaluated for the removal of 60 Hz power line interference (PLI), a common narrowband noise source introduced by electrical equipment and hospital power systems. PLI significantly contaminates ECG recordings by superimposing a periodic sinusoidal component over the cardiac waveform, potentially distorting amplitude measurements and affecting automated diagnostic systems.

As presented in Table 2, the algorithm achieved remarkable noise suppression across all selected records. The average SNR increased from 11.93 dB before filtering to 36.01 dB after filtering, corresponding to a substantial mean improvement of 24.08 dB. Record 100 exhibited the highest enhancement (29.89 dB), while even the lowest improvement (16.1 dB for record 228) indicates strong interference attenuation. Importantly, the correlation coefficient remained 1.0 for all records, demonstrating near-perfect preservation of the original ECG morphology. This indicates that the adaptive filter effectively eliminated the narrowband 60 Hz component without distorting clinically relevant features such as QRS amplitude and ST segments. These results confirm the algorithm's robustness and suitability for high-precision clinical and real-time ECG monitoring applications.

Table 2: SNR Improvement and Correlation Coefficient for PLI

Record	**SNR before (dB)**	**SNR after (dB)**	**Improvement (dB)**	**Correlation Coefficient**
100	8.05	37.94	29.89	1.0
105	14.69	40.08	25.39	1.0
108	8.75	31.6	22.85	1.0
203	12.66	38.85	26.19	1.0
228	15.49	31.59	16.1	1.0
Avg	**11.93**	**36.01**	**24.08**	**1.0**

4. Discussion

The GA-tuned SD-LMS filter demonstrates substantial advantages over conventional filtering methods by effectively preserving essential ECG waveform characteristics necessary for accurate diagnostics, consistent with prior adaptive filtering studies (Hassan et al., 2014). Unlike traditional filters, which often struggle to balance noise removal with signal fidelity, the GA-tuned SD-LMS filter dynamically adjusts to varying noise profiles, ensuring that key ECG features—such as the P wave, QRS complex, and T wave—remain intact. This preservation is crucial in clinical settings where even small distortions can lead to misinterpretation of cardiac events, impacting the diagnosis of arrhythmias, ischemic changes, and other cardiac abnormalities. By tuning the step size parameter (μ) through a Genetic Algorithm (GA), the GA-tuned SD-LMS filter provides an optimized balance between noise suppression and signal fidelity, a challenge for many traditional methods that rely on fixed filter parameters.

The adaptability of the GA-tuned SD-LMS filter is a major asset, especially for non-stationary noise sources such as baseline wander (BLW) and power line interference (PLI). BLW and PLI are common in ECG recordings and can vary in intensity and frequency over time, making them difficult to filter using static parameters. The GA-based optimization continuously fine-tunes the filter's parameters in real-time, ensuring that the filter responds to changes in noise characteristics as they occur. This capability makes the GA-tuned SD-LMS filter particularly suitable for applications in dynamic environments, such as ambulatory monitoring and stress testing, where patient movement or external electrical interference may introduce variable noise. The real-time adaptability of the GA-tuned SD-LMS filter enables more accurate and reliable ECG monitoring in these situations, improving diagnostic confidence.

In addition to its application in clinical and diagnostic settings, the GA-tuned SD-LMS filter holds promise for future integration into wearable and portable ECG monitoring devices. As wearable healthcare technology advances, there is a growing demand for lightweight, low-power filtering solutions capable of real-time signal processing. Traditional filtering methods can be computationally demanding and may drain battery life quickly, limiting the feasibility of continuous monitoring. In contrast, the GA-tuned SD-LMS filter's efficient noise reduction and adaptive capabilities make it a strong candidate for embedded systems, where power consumption and computational load must be minimized without sacrificing accuracy.

Looking forward, one area of future research could be the implementation of the GA-tuned SD-LMS filter on hardware platforms such as Field Programmable Gate Arrays (FPGAs) or Application-Specific Integrated Circuits (ASICs). These hardware platforms allow for fast, parallel processing and can further reduce power consumption, enabling the deployment of the GA-tuned SD-LMS filter in energy-efficient, real-time monitoring devices. FPGAs, in particular, offer the flexibility to adjust the filter's parameters through reprogramming, making them ideal for adaptive filtering applications that must respond to changing noise environments. Implementing the GA-tuned SD-LMS filter on an FPGA could enhance its responsiveness and allow for continuous real-time ECG monitoring in wearable devices with extended battery life.

Another potential research direction involves exploring more advanced GA configurations and hybrid optimization techniques. For example, combining GA with other optimization methods, such as Particle Swarm Optimization (PSO) or Simulated Annealing (SA), could further refine the step size tuning and improve convergence speed. These hybrid approaches may yield even better noise suppression and adaptability, enhancing the filter's effectiveness across diverse noise scenarios.

In summary, the GA-tuned SD-LMS filter represents a significant step forward in ECG noise reduction, particularly in real-time and portable applications. By preserving signal integrity while adapting to various noise profiles, it supports accurate diagnostics and opens the door to new possibilities in wearable health technology, remote monitoring, and mobile health applications. Future research in hardware implementation and hybrid optimization could further advance this technology, making it a powerful tool for improving patient care in both clinical and home settings (Haykin, 2002).

5. Conclusion

The GA-tuned SD-LMS filter is highly effective in significantly reducing baseline wander (BLW) and power line interference (PLI) noise in electrocardiogram (ECG) signals, addressing two of the most prevalent and disruptive noise sources in cardiac diagnostics. The ability to remove these noise components without compromising the integrity of the ECG signal is a critical advancement, as BLW and PLI can obscure key diagnostic features, such as the P wave, QRS complex, and T wave, making it difficult to assess cardiac health accurately. The filter's superior performance in noise reduction is demonstrated by substantial improvements in Signal-to-Noise Ratio (SNR) and correlation coefficients across various ECG records, showcasing its ability to enhance signal clarity while preserving essential diagnostic information.

BLW, caused by patient movement and respiration, introduces low-frequency noise that shifts the baseline of the ECG, potentially masking important features. The GA-tuned SD-LMS filter effectively suppresses this noise, achieving an average SNR improvement of 10.754 dB. This improvement ensures that critical features of the ECG remain clear and measurable, enabling more accurate detection of conditions like arrhythmias and ischemic episodes. Similarly, the filter's ability to mitigate PLI, which arises from interference at 50 or 60 Hz due to AC power sources, results in an average SNR improvement of 24.08 dB. This high-frequency noise can distort ECG waveforms, but the GA-tuned SD-LMS filter removes it while maintaining a high correlation coefficient close to 1.00. These metrics indicate that the filtered signals are highly faithful to the original, noise-free ECG signals, which is vital for reliable diagnostic applications.

The robustness of the GA-tuned SD-LMS filter makes it highly suitable for clinical environments, where the quality of ECG signals is paramount. Noise-free ECG signals are essential for diagnosing a wide range of cardiac conditions, including atrial fibrillation, ventricular tachycardia, and myocardial infarction. Additionally, the filter's adaptability to varying noise levels makes it well-suited for use in dynamic settings, such as during stress tests or exercise monitoring, where noise can fluctuate significantly.

Beyond traditional clinical settings, the GA-tuned SD-LMS filter is particularly advantageous for remote monitoring and wearable technologies. Wearable ECG devices are increasingly being used for continuous cardiac monitoring, providing valuable insights into a patient's heart health over extended periods. However, these devices are often used in environments where noise is unavoidable, such as during physical activity or in the presence of electrical devices. The ability of the GA-tuned SD-LMS filter to dynamically adjust to changing noise conditions ensures that these wearable devices can deliver high-quality, noise-free ECG signals, enhancing their diagnostic accuracy and reliability.

Moreover, the filter's computational efficiency makes it ideal for integration into resource-constrained platforms, such as portable and battery-powered devices. By leveraging a Genetic Algorithm (GA) to optimize the step size parameter, the filter achieves fast convergence and effective noise suppression without imposing significant computational overhead. This efficiency is crucial for wearable applications, where power consumption and processing speed are key considerations.

In the context of telemedicine and home healthcare, the GA-tuned SD-LMS filter can play a transformative role. With the increasing demand for remote patient monitoring, particularly for individuals with chronic heart conditions, ensuring the quality of transmitted ECG data is critical. By providing noise-free ECG signals, the GA-tuned SD-LMS filter enables clinicians to make more accurate assessments based on remotely collected data, reducing the need for frequent in-person visits and improving patient outcomes.

In conclusion, the GA-tuned SD-LMS filter represents a significant advancement in ECG noise reduction technology. Its ability to suppress BLW and PLI noise while preserving the diagnostic features of the ECG signal makes it an invaluable tool for both clinical and wearable applications. The demonstrated improvements in SNR and correlation coefficients highlight its effectiveness in maintaining signal integrity, paving the way for broader adoption in real-time monitoring, remote diagnostics, and wearable health technologies. This innovation not only supports more accurate diagnostics but also enhances the accessibility and quality of cardiac care in diverse healthcare settings.

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