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Noise Performance Analysis and Noise Reduction of Electrocardiogram Signals for Heart Patients Using Parks-McClellan Based Optimized Window Function

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A B S T R A C T :

Electrocardiogram (ECG) signals are widely used for diagnosing and monitoring cardiovascular diseases, but their diagnostic accuracy is often compromised by various noise interferences like baseline wander, powerline interference, muscle artifacts, and electrode movement. These distortions obscure clinically significant characteristics of the ECG waveform, such as the T wave, QRS complex, and P wave, thereby increasing the risk of misdiagnosis. This research concentrates on evaluating the performance of noise in ECG signals and implementing an optimized filtering technique based on a Kaiser window in a Finite Impulse Response (FIR) filter enhanced by the Parks–McClellan algorithm. ECG data were acquired using the OpenBCI Cyton biosensing board and processed in MATLAB. Different filtering techniques—including high-pass, band-pass, and notch filters—were designed and evaluated. The proposed PMC-optimized Kaiser window was compared against conventional FIR filters to assess its effectiveness in reducing noise while preserving ECG morphology. Performance was evaluated Using measurements like Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Signal-to-Noise Ratio (SNR). The results demonstrated that the PMC-optimized Kaiser window significantly improved noise suppression, yielding higher SNR and lower RMSE compared to traditional filters. The optimized filters preserved the critical diagnostic features of the ECG with minimal distortion, confirming their suitability for clinical and real-time applications. This work contributes to the development of more robust and reliable ECG noise reduction techniques, with potential applications in wearable health monitoring systems and clinical diagnostics for improved patient outcomes.

Keywords: Electrocardiogram (ECG), Noise Reduction, FIR Filter, Kaiser Window, Parks–McClellan Algorithm, Signal Processing, Clinical Diagnostics.

1. INTRODUCTION

1.1 Background of the study

An essential diagnostic tool in cardiology for tracking and assessing the electrical activity of the heart is the electrocardiogram (ECG). By monitoring the heart's electrical impulses, ECG data provide significant insights into the heart's rhythm, pace, and overall functionality. The importance of ECG signals in diagnosing and managing heart diseases cannot be overstated.

One of the main health issues and the world's leading cause of death is cardiovascular disease. With the advancement of contemporary culture, wearable technology has become extensively utilized in home medical monitoring and may be applied to a variety of physiological metrics and health condition scenarios. ECG devices play a crucial role in at-home medical treatment and are useful for monitoring cardiovascular conditions. The ECG signal is a low-frequency, low-amplitude signal that varies between 0.05 and 150 Hz in frequency and between 0.01 and 4 mV in amplitude. It can be readily tainted by a variety of interference, including electromyography (EMG) and power-line noise. (Kumar et al., 2017; Liu et al., 2022).

An ECG signal is often shown as a succession of waves, including the P wave, QRS complex, and T wave, with each wave indicating separate stages of the cardiac cycle. Atrial depolarization is represented by the P wave, ventricular depolarization by the QRS complex, and ventricular repolarization by the T wave. Analysing these waves helps clinicians detect a wide range of cardiac abnormalities, including arrhythmias, myocardial infarction, and electrolyte imbalances (Kumar et al., 2017)

Due to their extremely low power, ECG signals are frequently tainted with noise during recording. Suppressing these disturbances is crucial for interpreting any heart condition since they distort the ECG signal in many frequency bands. Because of its basic properties, such as low power and low frequency, de-noising the ECG signal is crucial and a crucial step in the difficult process of diagnosing diseases. ECG signal noises can be broadly classified into four groups based on their nature and frequency range. (i) electrode motion; (ii) base line wander; (iii) power line interference; and (iv) electromyography (EMG) or muscle noise (Boyer et al., 2023; Liu et al., 2022).

To solve the problem, signal processing techniques such adaptive filtering, wavelet transform, empirical mode decomposition (EMD), and notch filter are suggested for noise reduction. Artificial neutral networks (ANN) have been utilized in the reconstruction of high-quality ECG signals due to the recent rapid advancement of neural network technology (Hussein et al., 2022).

1.1.1 Challenges in ECG and the state-of-art Technology

ECG signals play a pivotal role in both acute and chronic cardiac care. They are essential in emergency settings for the fast detection of life-threatening circumstances such as heart attacks (myocardial infarctions) and arrhythmias. In chronic care, ECG monitoring aids in the management of conditions like heart failure and atrial fibrillation, allowing for timely interventions and adjustments to treatment plans.

The non-invasive nature of ECG makes it an accessible and widely used diagnostic tool. It is routinely employed in various clinical settings, from primary care offices to specialized cardiac units. The ability to continuously monitor ECG signals through Holter monitors and wearable devices has further enhanced its utility, providing continuous data that can be analysed for long-term heart health assessment.

Despite its diagnostic value, the accuracy and reliability of ECG signal interpretation can be significantly compromised by various sources of noise. Noise in ECG signals can originate from multiple internal and external factors, affecting the clarity of the recorded signals. Common sources of noise include:

i. Baseline Wander: Low-frequency noise induced by patient movement, respiration, and electrode positioning difficulties, leading to fluctuations in the baseline of the ECG signal.
ii. Power Line Interference: High-frequency noise from electrical devices and power lines, usually at 50 or 60 Hz, which can distort the ECG signal.
iii. Muscle Noise (Electromyographic Noise): Noise generated by muscle contractions, especially during physical activity or involuntary muscle movements, leading to high-frequency artifacts.
iv. Electrode Motion Artifacts: Noise resulting from the movement of electrodes relative to the skin, often due to patient movement or poor adhesion, causing transient disturbances in the signal (Ekundayo & Nyavor, 2024).

Accurate interpretation of ECG signals is crucial for effective cardiac care. However, the presence of noise can obscure important clinical information, leading to misdiagnosis or missed diagnosis of critical conditions. For instance, baseline wander can mimic or mask ST-segment deviations, which are vital for diagnosing myocardial infarction. Similarly, power line interference and muscle noise can distort the waveform, complicating the identification of arrhythmias and other anomalies (Patil et al., 2023).

Noise analysis and reduction are, therefore, essential components of ECG signal processing. By understanding the sources and characteristics of noise, effective strategies can be developed to mitigate their impact, enhancing signal-to-noise ratio and improving accuracy of ECG interpretations (Ayodele et al., 2024). This thesis aims to analyse the noise performance in ECG signals and evaluate various noise reduction techniques to propose an optimized method for improving ECG signal quality for heart patient.

1.1.2 State-of-the-Art Approaches

i. Personalized Filtering Algorithms: Advanced machine learning models and adaptive filtering systems can be tailored to individual patients' unique ECG signal patterns and noise profiles. This approach improves noise suppression accuracy without losing diagnostic information.
ii. Wearable Device Customization: Emerging wearable technologies with customizable hardware and software enable better signal acquisition by adjusting parameters such as electrode placement, sampling rates, and noise neutralization for specific patient needs.

iii. Integration of Multimodal Sensors: Combining ECG data with other bio signals (e.g., photoplethysmography or respiratory monitoring) helps create a more robust and noise-resilient dataset. Cross-referencing physiological data can aid in distinguishing noise from true cardiac activity.

iv. Real-Time AI Assistance: Artificial intelligence systems can learn from patient-specific patterns in real-time, dynamically adjusting processing algorithms to adapt to changes in noise levels or cardiac signal behavior.

By addressing patient-specific factors and leveraging state-of-the-art personalized technologies, the reliability of ECG signal analysis can be significantly enhanced, leading to better diagnostics and improved healthcare outcomes (Velic et al., 2013).

1.2 Problem Statement

The accurate interpretation of Electrocardiogram (ECG) signals is vital for the effective diagnosis, and monitoring of heart patients. However, the presence of noise in ECG signals presents a significant challenge, potentially compromising the reliability and precision of cardiac assessments. Noise, This may come from a number of sources, including electrical interference, movement anomalies, and metabolic variability, can obscure critical features of the ECG waveform, leading to misinterpretations or misdiagnoses.

This research aims to analyse the noise performance of ECG signals in order to get clear insight into how noise impacts their accuracy and reliability. By systematically investigating the types, sources, and effects of noise on ECG signals, this study seeks to identify specific challenges in ECG interpretation and proffer solutions by mitigating noise-related issues and enhance the overall quality of ECG-based cardiac care.

2.0 MATERIALS AND METHOD

2.2 Materials and Tools

The materials and tools needed for this research are:

- Laptop computer
- MATLAB/Simulink
- Cyton Biosensing Board
- OpenBCI

2.3 Data Collection

For this research, the raw ECG signals are collected through the OpenBCI Cyton biosensing. which is known for high-quality, annotated ECG recordings, which offer a variety of ECG signals with diverse characteristics and noise profiles

2.4 Process flow of the system and Flowchart of Parks – McClellan Algorithm

The process flow of the system is shown below:

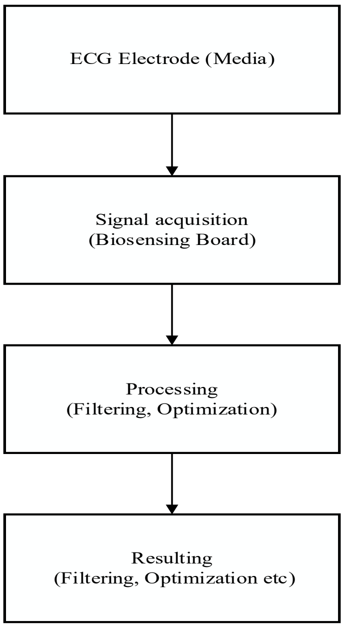


Fig.1- Process flow

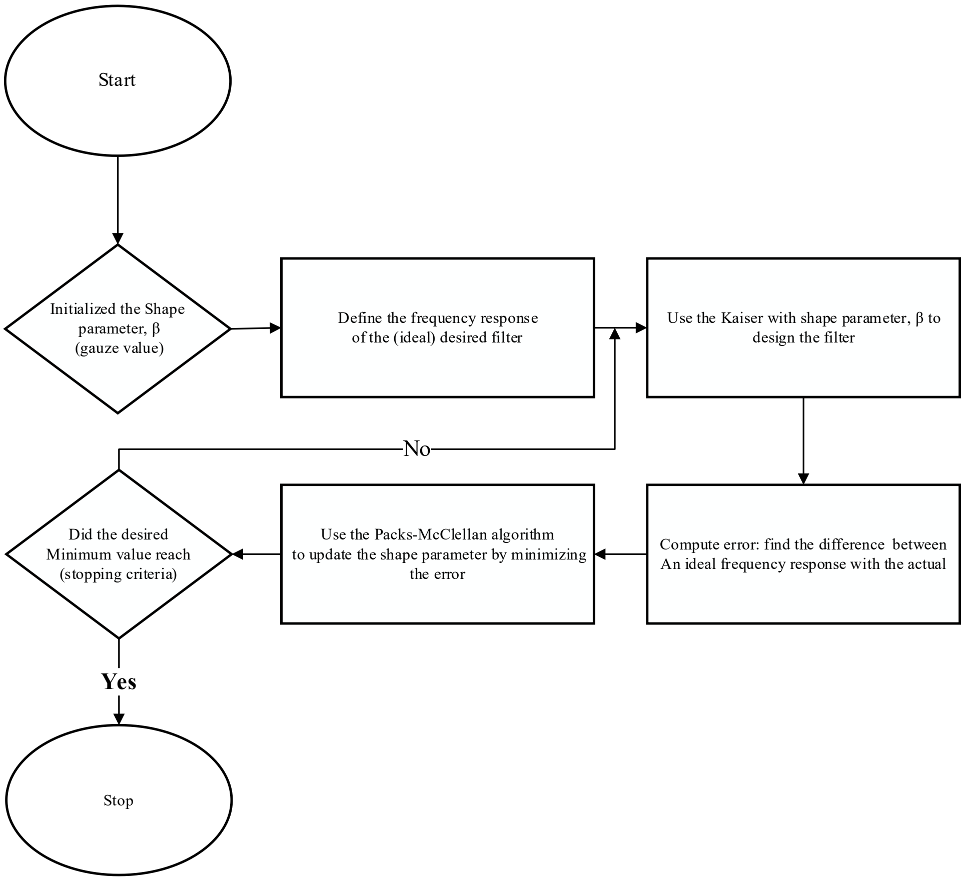


Fig. 2- Flowchart of Parks – McClellan Algorithm

2.5 Tools Used for Noise Analysis

1. Baseline Wander Removal: A high-pass filter having a cutoff frequency of 0.5 Hz was implemented to reduce baseline drift. The high-pass filtering transfer function is defined as:

$$H(f) = \frac{f}{\sqrt{f^2+f_c^2}} \qquad (1)$$

where, f_c is the cutoff frequency and f is the frequency.

2. Powerline Interference Filtering: A notch filter cantered at 50 Hz (or 60 Hz, depending on the location of the data source) was used to suppress powerline interference. The notch filter transfer function is expressed as:

$$H(f) = 1 - \frac{\gamma^2}{\gamma^2+(f-f_0)^2} \qquad (2)$$

where f_0 represents the notch frequency (50 Hz or 60 Hz), and γ is the bandwidth of the notch.

3. Muscle Noise Reduction: A low-pass filtering with cutoff frequency of 100 Hz was applied so that to eliminate high-frequency muscle noise while preserving the relevant components of the ECG signal. The transfer function for the low-pass filter is:

$$H(f) = \frac{f_c^2}{f_c^2+f^2} \qquad (3)$$

where f, is the frequency while f_c is the cutoff frequency (100 Hz in this case).

By applying these filtering techniques, the noise levels were significantly reduced while ensuring that the main elements of the ECG signals, such as the P, QRS, and T waves, were maintained. The performance of the noise removal process was evaluated using the SNR before and after filtering.

2.5.1 Formulae for Noise Quantification and Filtering

In addition to SNR, additional measures like Mean Squared Error (MSE) were used to quantify the effect of noise before and after filtering. The MSE difference of the initial and filtered signals is calculated as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{4}$$

where x_i is the initial, and $\hat{x}_i$ is the filtered signal, while N is the total amount of data.

2.6 Noise Reduction Techniques Evaluation

2.6.1 High-Pass Filtering for Baseline Wander Removal

Baseline wander is a low-frequency noise caused primarily by respiration and patient movement. A high-pass filter with a cutoff frequency of roughly 0.5 Hz is employed to remove this noise while maintaining the higher-frequency components of the ECG signal, including the P, QRS, and T waves. The transfer function for a high-pass filter is given by:

$$H(f) = \frac{f}{\sqrt{f^2+f_c^2}} \tag{5}$$

where f, is the frequency while f_c is the cutoff frequency (0.5 Hz in this case). The cutoff frequency is chosen carefully to eliminate baseline wander while retaining diagnostically relevant features of the ECG.

2.6.2 Notch Filtering for Powerline Interference

Powerline interference is a frequent sort of noise created by electrical sources and usually occurs at 50 Hz (in Europe) or 60 Hz (in the US). A notch filter is employed to attenuate this specific frequency without influencing the other components of the ECG signal. The transfer function for a notch filter is represented as:

$$H(f) = 1 - \frac{\gamma^2}{\gamma^2+(f-f_0)^2} \tag{6}$$

where f_0 is the notch frequency (50 or 60 Hz), and γ is the bandwidth of the filter, which determines the width of the frequency range affected by the filter. The notch filter is highly effective at suppressing narrow-band interference such as powerline noise.

2.6.3 Low-Pass Filtering for Muscle Noise (EMG) Reduction

Muscle noise, or electromyographic (EMG) noise, is typically high-frequency noise caused by muscle contractions. To mitigate this type of noise, a low-pass filter with a cutoff frequency of roughly 100 Hz is applied. This helps remove high-frequency noise while preserving the ECG signal components, particularly the QRS complex, which contains important diagnostic information.

The low-pass filter's transfer function is given by:

$$H(f) = \frac{f_c^2}{f_c^2+f^2} \tag{7}$$

where f_c is the cutoff frequency (set to 100 Hz). This filter is designed to reduce muscle noise while minimizing distortion to the ECG signal.

2.6.4 Implementation of Noise Reduction Techniques on ECG Data

The noise reduction techniques discussed above were implemented using MATLAB. ECG signals from the OpenBCI cyton board were pre-processed, and each noise reduction technique was applied to the recordings. The implementation followed these steps:

1. Preprocessing: The raw ECG data were loaded, and each signal was segmented to focus on noisy portions.

2. Filtering: High-pass, notch, and low-pass filters were designed in MATLAB using the butter function to create Butterworth filters for each type of noise. The Kaiser window function was used to apply the filters to the ECG signals.

3. Wavelet Denoising: The wden function in MATLAB was used to apply wavelet-based denoising to the ECG signals.

4. Adaptive Filtering: The LMS adaptive filter was implemented using a custom MATLAB script, and the adaptfilt toolbox was used to train the filter on noisy ECG signals.

5. Evaluation: The effectiveness of the methods for reducing noise was evaluated using statistical metrics to assess the quality of the denoised signals.

2.7 Evaluation Metrics

The effectiveness of the noise reduction techniques was evaluated using several performance metrics, which measured both the quality of the denoised signals and the preservation of diagnostically important ECG features.

2.7.1 Criteria for Evaluating Noise Reduction Techniques

The primary criteria for evaluating noise reduction techniques are:

1. Signal Preservation: The ability of the technique to retain critical ECG features such as the P wave, QRS complex, and T wave after noise removal.

2. Noise Suppression: The effectiveness of the technique in reducing different types of noise, including baseline wander, powerline interference, and muscle noise.

3. Computational Efficiency: The speed and resource usage of the technique, particularly important for real-time applications.

3.0 PERFORMANCE METRICS

The following metrics were used to evaluate the noise reduction techniques:

1. Signal-to-Noise Ratio (SNR): The SNR is a common measure used to quantify the amount of noise relative to the ECG signal before and after denoising. It is calculated as:

$$SNR = 10.log_{10}(\frac{P_{signal}}{P_{noise}}) \quad (9)$$

where P_{signal} is the power of the ECG signal, and P_{noise} is the power of the noise.

2. Root Mean Square Error (RMSE): RMSE quantifies the error between the original and denoised signals, calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \quad (10)$$

Where x_i is the original signal, $\hat{x}_i$ is the denoised signal, and N is the total number of samples.

3. Mean Squared Error (MSE): MSE measures the average squared difference between the original and denoised signals:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \quad (11)$$

MSE is a useful metric for evaluating how much distortion has been introduced during noise reduction.

4. The Kaiser window function is given by:

$$w_k(n) = \begin{cases} \frac{I_0\left\{\alpha\sqrt{1-\left[\frac{2n}{N-1}\right]^2}\right\}}{I_0(\alpha)} \; for\ |n| \leq \frac{(N-1)}{2}; \\ 0, \quad otherwise, \end{cases} \quad (12)$$

$$where,\ \alpha\ is\ an\ independent\ variable\ which\ is\ adjustable\ given\ by\ James\ Kaiser,$$

$$I_{0(x)}\ is\ the\ modified\ zeroth\ order\ Bessel\ functions\ of\ the\ first\ kind.$$

5. The parameter β can be described as:

$$\beta = \alpha\left[1 - \left(\frac{2n}{M-1}\right)^2\right]^{\frac{1}{2}} \qquad (13)$$

4.0 RESULTS

4.1 Introduction

The research findings are presented and discussed in this section on noise performance analysis and reduction in ECG signals using a Parks–McClellan optimized window function. Building on earlier methodologies, it focuses on the implementation and evaluation of the proposed noise reduction techniques.

The main goal is to assess how effectively the Kaiser window optimized by the Parks–McClellan algorithm enhances ECG signal quality while preserving key diagnostic features (P wave, QRS complex, and T wave). ECG data collected via the OpenBCI Cyton board were filtered using high-pass, band-pass, and notch filters designed with the optimized algorithm, and results were compared with conventional filtering methods.

The analysis includes both graphical (magnitude, impulse, and phase responses; time-domain signal comparisons) and quantitative evaluations using SNR, RMSE, and MSE metrics. These comparisons demonstrate the superior noise suppression and signal clarity achieved with the optimized Parks–McClellan filters relative to traditional approaches.

4.2 Results and Discussion

Fig. 3- shows the numerical electrocardiogram (ECG) readout obtained from the OpenBCI Cyton biosensing board. The values represent raw signal data captured directly from the electrodes placed on the subject. Each numerical entry corresponds to the sampled electrical potential differences generated by the heart's activity at specific time intervals.

%OpenBCI Raw EEG Data				
%Number of channels = 8				
%Sample Rate = 250 Hz				
%Board = OpenBCI_GUI$BoardCytonSerial				
Sample Index	EXG Channel 0	EXG Channel 1	EXG Channel 2	EXG Channel 3
0.0	0.0	0.0	0.0	797.6890258789062
1.0	0.0	0.0	0.0	876.0765991210938
2.0	0.0	0.0	0.0	869.9969482421875
3.0	0.0	0.0	0.0	794.3139038085938
4.0	0.0	0.0	0.0	738.0322265625
5.0	0.0	0.0	0.0	783.7191772460938
6.0	0.0	0.0	0.0	862.0620727539062
7.0	0.0	0.0	0.0	862.1067504882812
8.0	0.0	0.0	0.0	786.0661010742188
9.0	0.0	0.0	0.0	729.9185180664062
10.0	0.0	0.0	0.0	777.7512817382812
11.0	0.0	0.0	0.0	862.4867553710938
12.0	0.0	0.0	0.0	861.816162109375
13.0	0.0	0.0	0.0	785.10498046875
14.0	0.0	0.0	0.0	725.5152587890625

15.0	0.0	0.0	0.0	776.41015625
16.0	0.0	0.0	0.0	870.3768920898438

Fig. 3- Numerical ECG readout from the open BCI cyton board

This numerical output forms the foundation for subsequent signal processing and analysis. By converting the raw electrical activity into discrete numerical values, the system enables filtering, visualization, and performance evaluation of ECG signals under varying noise conditions. The data captured here provides a baseline reference, allowing comparison between the original unprocessed signals and those enhanced through noise reduction techniques such as high-pass, band-pass, and notch filters optimized using the Parks–McClellan algorithm.

4.2.1 Magnitude Responses of the Designed Filters

Fig. 4- presents the magnitude responses of three Finite Impulse Response (FIR) filters designed with the Kaiser window and optimized using the Parks–McClellan algorithm. These plots demonstrate how each filter selectively attenuates unwanted frequency components while preserving the diagnostically relevant frequency range of the ECG signal.

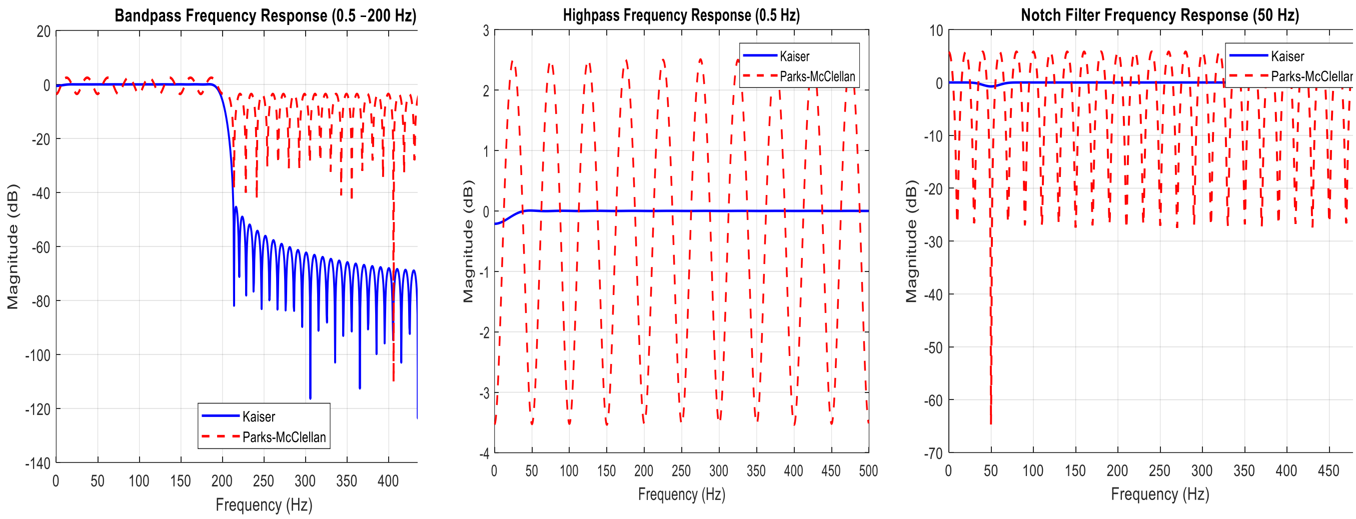


Fig. 4- (a) Magnitude response of band pass filter (BPF);

(b) Magnitude response of high pass filter (HPF);

(c) Magnitude response of band reject filter (BRF).

Fig. 4- (a): Band-Pass Filter (BPF) – The band-pass filter response highlights the frequency band within which ECG signals are preserved (typically 0.5–100 Hz), while attenuating both low-frequency baseline wander and high-frequency muscle artifacts. This ensures that the essential components of the ECG, including the P wave, QRS complex, and T wave, are maintained.

(b): High-Pass Filter (HPF) – The high-pass filter response shows the removal of very low-frequency noise, particularly baseline wander (below 0.5 Hz), which is commonly caused by respiration and body movement. By eliminating these drifts, the overall clarity of the ECG waveform is enhanced.

(c): Band-Reject (Notch) Filter (BRF) – The band-reject filter demonstrates its effectiveness in suppressing narrowband interference, especially powerline noise at 50/60 Hz. This filter allows the ECG signal outside the interference frequency to pass unaffected, ensuring minimal distortion of important cardiac features.

Together, these magnitude responses validate the theoretical design of the filters, showing that each plays a complementary role in addressing the major sources of noise in ECG recordings. The next sections compare the performance of these filters when applied to actual ECG signals.

4.2.2 Impulse Responses of the Designed Filters

Fig. 5- illustrates the impulse responses of the FIR filters designed using the Kaiser window and optimized by the Parks–McClellan algorithm. The impulse response of a filter is a critical indicator of its stability, phase linearity, and ability to accurately process input signals without distortion.

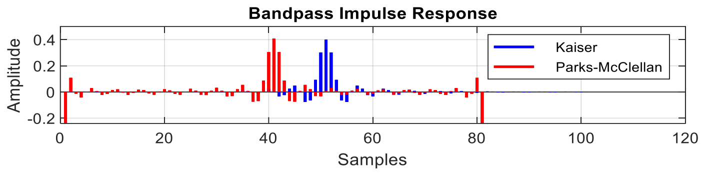
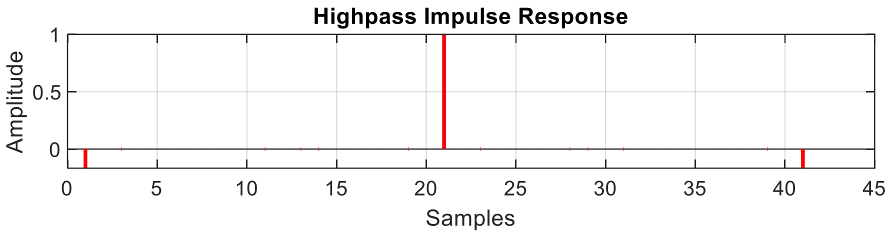
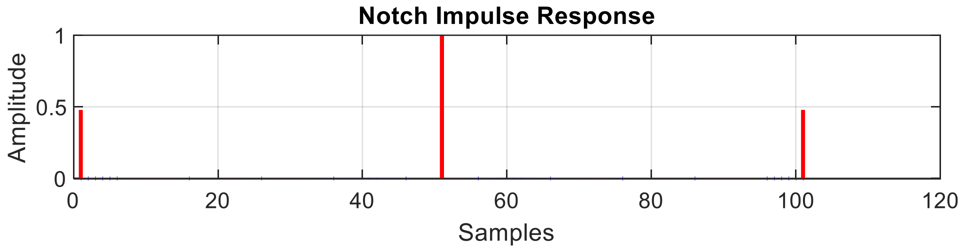


Fig. 5- (a) Impulse response of Band pass filter (BPF);



(b) Impulse response of high pass filter (HPF);



(c) Impulse response of band reject filter (BRF).

Fig. 5- (a): Band-Pass Filter (BPF) – The impulse response of the BPF shows a symmetric pattern around its centre, confirming the linear-phase property of the FIR filter. This ensures that all frequency components of the ECG signal within the passband are delayed equally, thereby preserving the waveform morphology of the P wave, QRS complex, and T wave.

(b): High-Pass Filter (HPF) – The impulse response of the HPF exhibits alternating positive and negative values that gradually decay, reflecting its ability to suppress low-frequency components (such as baseline wander) while maintaining higher-frequency cardiac features.

(c): Band-Reject Filter (BRF) – The impulse response of the BRF reveals the characteristics of a notch filter designed to eliminate a specific narrowband frequency, in this case, powerline interference (50/60 Hz). The response confirms that the filter selectively rejects this frequency while allowing other frequency components of the ECG signal to pass with minimal distortion.

These impulse responses collectively validate the effectiveness of the filter design, ensuring that the applied filters meet the necessary requirements for stable and distortion-free ECG signal processing.

4.1.3 Comparison of Unprocessed and FIR Band-Pass Filtered ECG Signal with Kaiser Window

Fig. 6- presents a comparison between the raw ECG signal and the signal processed using a Finite Impulse Response (FIR) band-pass filter designed with the Kaiser window. The band-pass filter is intended to preserve the diagnostically relevant ECG frequency range (0.5–100 Hz) while attenuating both low-frequency and high-frequency noise.

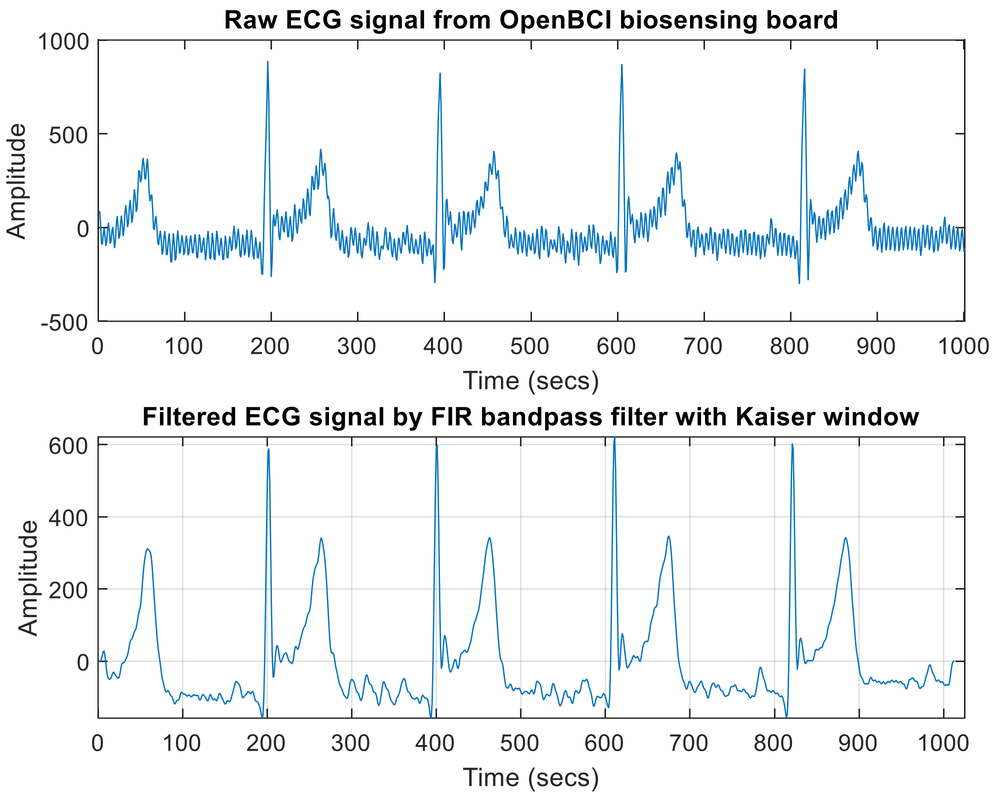


Fig. 6-Comparison (a) Unprocessed ECG Signal; (b) FIR banpass filtering with Kaiser window.

Fig. 6- (a): Unprocessed ECG Signal – The raw ECG waveform is distorted by multiple noise sources, including baseline wander at low frequencies and high-frequency muscle noise. These distortions reduce the visibility of important clinical features such as the P wave, QRS complex, and T wave.

(b): FIR Band-Pass Filtered ECG Signal – After applying the band-pass filter, the signal is notably cleaner. Low-frequency drifts and high-frequency interferences are effectively suppressed, while the essential ECG morphology is preserved. The P wave, QRS complex, and T wave become more distinguishable, improving the overall diagnostic clarity of the signal.

This result validates the effectiveness of the FIR band-pass filter with Kaiser window in addressing multiple sources of noise simultaneously, thereby enhancing ECG signal quality for accurate interpretation.

4.2.4 Comparison of Unprocessed ECG Signal and Powerline Filtered ECG Signal

Fig. 7- compares the raw ECG signal with the output after applying a notch filter designed with the Kaiser window to remove powerline interference (50/60 Hz). Powerline noise is one of the most common sources of distortion in ECG signals, especially in clinical and laboratory environments where multiple electronic devices are in use.

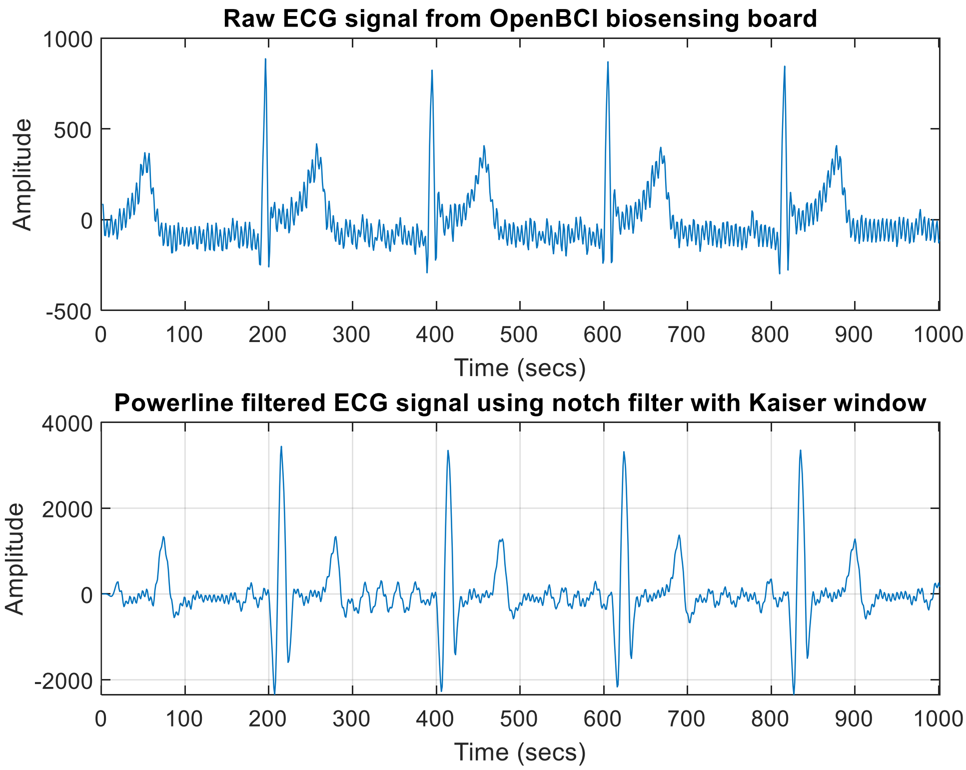


Fig. 7- Comparison (a) Unprocessed ECG Signal; (b) Powerline ECG Signal using notch filter with Kaiser window.

Fig. 7- (a): Unprocessed ECG Signal – The raw ECG signal shows sinusoidal interference superimposed on the cardiac waveform, resulting from electromagnetic coupling with power supply lines. This interference reduces the visibility of fine details such as the P wave and can complicate accurate QRS detection.

(b): Powerline Filtered ECG Signal – After applying the notch filter, the periodic 50/60 Hz interference is effectively suppressed while the essential features of the ECG, including the P wave, QRS complex, and T wave, remain intact. The improvement enhances diagnostic clarity without significantly altering the morphology of the signal.

This demonstrates the effectiveness of the Kaiser window–based notch filter in addressing narrowband noise sources like powerline interference while maintaining the diagnostic reliability of the ECG signal.

4.2.5 Comparison of FIR Band-Pass Filter with Kaiser Window and PMC Algorithm Optimized Kaiser Window

Fig. 8- compares the performance of two band-pass filter designs applied to ECG signals: the conventional FIR filter with a Kaiser window and the optimized FIR filter using the Parks–McClellan (PMC) algorithm. The objective of this comparison is to demonstrate the improvement achieved by introducing optimization into the window design.

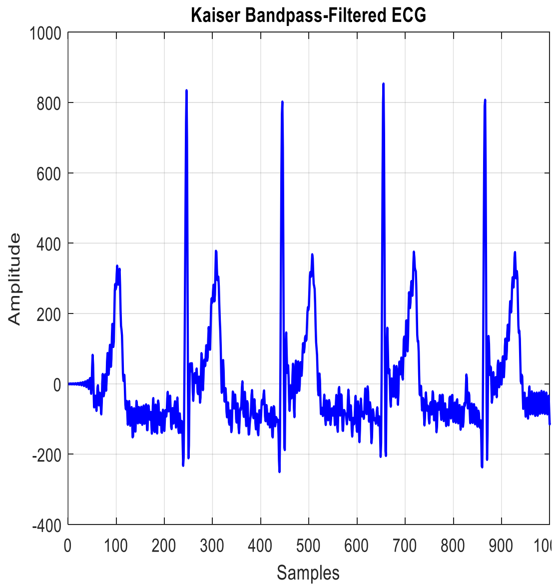
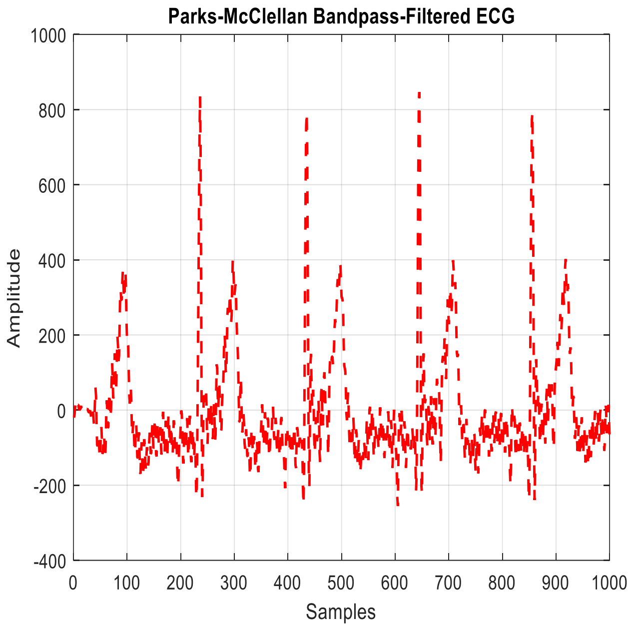


Fig. 11- Comparison (a) FIR banpass filter with Kaiser window;



(b) PMC algorithm optimized banpass Kaiser window.

Fig. 11- (a): FIR Band-Pass Filter with Kaiser Window – The signal filtered with a standard Kaiser window shows a reduction in noise components such as baseline wander and high-frequency artifacts. However, some residual distortion is still noticeable, and the signal-to-noise ratio (SNR) improvement is limited.

(b): PMC Algorithm Optimized Kaiser Window – After optimization with the Parks–McClellan algorithm, the filter exhibits superior performance. The ECG signal is cleaner, with sharper preservation of the P wave, QRS complex, and T wave. Noise suppression is more effective, and the waveform morphology remains intact, reflecting both higher SNR and lower root mean square error (RMSE).

This comparison validates the significance of the proposed approach, showing that the PMC-optimized Kaiser window provides a more robust filtering solution compared to the conventional method. It ensures improved diagnostic reliability in ECG analysis, especially in environments with high noise contamination.

5.0 CONCLUSIONS

From the study, the following conclusions were drawn:

1. White Gaussian Noise (WGN) negatively affects the accuracy and quality of ECG signals.

2. The Kaiser window-based FIR filter effectively improves the signal-to-noise ratio (SNR) and maintains ECG waveform quality.

3. The Parks-McClellan optimized FIR filter with a Kaiser window provides an efficient and reliable method for ECG noise reduction.

5,1 Contributions to Knowledge

This research makes the following contributions:

1. Demonstrated the effectiveness of a PMC-optimized Kaiser window in enhancing ECG signal quality compared to conventional FIR filters.

2. Established a framework for evaluating ECG noise reduction using both graphical (waveform analysis) and quantitative (SNR, RMSE, MSE) methods.

3. Proved that optimization of filter windows significantly improves ECG signal reliability by balancing noise suppression with diagnostic feature preservation.

4. Advanced the knowledge of ECG signal processing by providing evidence that optimized FIR filters can be integrated into wearable devices and clinical systems for real-time applications.

5. Bridged a research gap identified in the literature, where limited focus had been given to optimizing window functions for ECG filtering.

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