Middle East Journal of Applied Science & Technology (MEJAST)
Volume 6, Issue 2, Pages 131-143, April-June 2023

Performance Analysis of FIR Adaptive Filter Algorithms for Denoising Adult ECG Signals: A Comparative Study

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DOI: https://doi.org/10.46431/MEJAST.2023.6215

Article Received: 17 April 2023 *Article Accepted: 29 May 2023* *Article Published: 14 June 2023*

ABSTRACT

This paper describes a unique study that uses multiple FIR adaptive filter algorithms to denoise adult electrocardiogram (ECG) data. The study looks at how power line interference, external electromagnetic fields, random body motions, and breathing impact ECG measurement accuracy. The article takes a fresh look at Savitzky-Golay filtering techniques by implementing and evaluating them inside the FIR adaptive filter architecture. Matlab is used to evaluate the performance of the Affine projection FIR adaptive filter (AP), Direct-form Normalized least-mean-square FIR adaptive filter (NLMS), and Sliding-window Recursive least-squares FIR adaptive filter (SWRLS). The results show how different strategies compare in terms of performance and their influence on recorded waveform quality. The study extends to our understanding of the efficiency of FIR adaptive filter algorithms in decreasing ECG signal noise and helps us better understand their potential uses in ECG signal processing. Based on reliable ECG data, the research findings assist the development of new approaches for diagnosing aberrant cardiac rhythms and examining the origins of chest discomfort. The originality of this work comes in its thorough assessment, comparison, and unique use of Savitzky-Golay filtering techniques inside FIR adaptive filter algorithms, which contributes to the area of ECG signal denoising. According to a comparative investigation, the SWRLS FIR adaptive filter method improves ECG signal denoising by 91.53% noise reduction.

Keywords: Electrocardiogram (ECG); Denoising; FIR adaptive filter algorithms; Savitzky-Golay filtering; Adult ECG signals.

1. Introduction

Electrocardiogram (ECG) signals play a vital role in diagnosing cardiovascular conditions and monitoring the heart's electrical activity [1]. However, accurate analysis of ECG measurements can be challenging due to the presence of various sources of noise, including power line interference, external electromagnetic fields, random body movements, and respiration [2]. These noise sources can significantly affect the reliability and precision of ECG data, leading to potential misinterpretations and erroneous diagnoses.

In recent years, denoising techniques utilizing digital signal processing methods have emerged as effective tools for mitigating noise interference in ECG signals. Among these techniques, Finite Impulse Response (FIR) adaptive filter algorithms have shown promising capabilities in enhancing the quality and accuracy of ECG measurements. These algorithms aim to adaptively estimate and eliminate noise components from the recorded ECG waveforms, providing a cleaner representation of the underlying cardiac activity. Singh, Bhole, and Sharma (2017) present a review of adaptive filtration techniques for impulsive noise removal from electrocardiogram (ECG) signals. The authors emphasize the significance of ECG in diagnosing and analyzing heart disorders, highlighting the detrimental impact of noise on accurate diagnosis. They compare two adaptive filtering algorithms, namely Least Mean Squares (LMS) and Recursive Least Squares (RLS), in terms of their ability to remove impulsive noise from ECG signals. The study demonstrates that the RLS algorithm outperforms LMS in terms of signal-to-noise ratio improvement, stability of the ECG signal, and convergence speed, despite its higher complexity. The authors acknowledge the challenge of excessive mean square error resulting in signal distortion, suggesting it as a potential avenue for future research [3]. An and Stylios (2020) conducted a research on motion artifact reduction methods in wearable electrocardiogram (ECG) monitoring. The study compared various denoising techniques including finite impulse response (FIR) filters, infinite impulse response (IIR) filters, moving average filters, moving median filters, wavelet transform, empirical mode decomposition, and adaptive filters. The results demonstrated that adaptive filters outperformed other methods, particularly in handling abnormal ECG signals from patients with heart disease. The authors also explored the implementation of adaptive motion artifact reduction using the impedance pneumography signal as a reference input signal, which effectively reduced motion artifacts in the ECG signal. The findings highlight the efficacy of adaptive filtering in mitigating motion artifacts in wearable ECG monitoring [4]. Mohammad Reza Mohebbian, Mohammad Wajih Alam, Khan A. Wahid, and Anh Dinh (2020) present a novel algorithm for single-channel high noise level ECG deconvolution. Traditional noise cancellation techniques are not efficient for non-stationary ECG signals, making adaptive filters more suitable. However, adaptive algorithms require a model of the noise or desired signal. The proposed algorithm utilizes fixed-point convolution kernel compensation to find a model for an adaptive filter and employs the recursive least square method for ECG signal deconvolution. The algorithm demonstrates improved performance in denoising ECG signals, particularly in scenarios with a negative signal-to-noise ratio. Additionally, the algorithm is effective in blind source separation applications, such as extracting fetal ECG from maternal ECG using a single thoracic channel. The results highlight the algorithm's ability to accurately extract the QRS complex of fetal ECG, comparable to methods that use abdominal channels [5]. Abel Jaba Deva Krupa, Samiappan Dhanalakshmi, N.L. Sanjana, Naveen Manivannan, Ramamoorthy Kumar, and Saswati Tripathy (2021) propose a novel algorithm for extracting the fetal electrocardiogram (FECG) from single-channel abdominal electrocardiogram (ECG) signals. The algorithm combines fractional Fourier transform (FrFT) and wavelet analysis to achieve accurate extraction of the fetal ECG and estimation of the fetal heart rate. The abdominal signals are preprocessed to suppress the maternal ECG using FrFT and maximum likelihood estimate. The estimated maternal signal is then removed, and the residue is processed using wavelet decomposition to obtain a clean fetal ECG. The proposed method demonstrates high accuracy in FECG extraction, achieving 98.12% accuracy, 98.85% sensitivity, 99.16% positive predictive value, and 99.42% F1 measure. The results validate the effectiveness of the algorithm using signals from various databases and real-time acquisitions. This approach holds promise for non-invasive fetal cardiac monitoring during pregnancy [6]. Abel Jaba Deva Krupa, Samiappan Dhanalakshmi, and Ramamoorthy Kumar (2023) present a comprehensive survey on signal processing and machine learning techniques for non-invasive fetal electrocardiogram (ECG) extraction. The paper highlights the lag in morphological analysis of fetal ECG signals compared to adult ECG signals and emphasizes the importance of non-invasive fetal ECG monitoring for assessing fetal health. The primary challenge in this approach is the low signal-to-noise ratio (SNR) due to dominant maternal ECG and other interferences in the abdominal ECG (AECG) signals. The survey provides a thorough review of existing techniques for fetal ECG extraction from AECG signals, covering topics such as fetal ECG modeling, challenges related to electrode placements, morphological analysis of extracted fetal ECG, and evaluation metrics for performance measurement. The paper aims to enhance researchers' understanding of this field and guide future directions in processing AECG signals [7]. This article presents a comprehensive study that focuses on the denoising of adult ECG signals using various FIR adaptive filter algorithms. The primary objective of this research is to address the challenges posed by different sources of noise and investigate the effectiveness of these algorithms in reducing noise interference in adult ECG measurements. It highlights the importance of accurate ECG measurements in analyzing abnormal heart rhythms and investigating chest pains. The novelty lies in the specific focus on the implementation and analysis of Savitzky-Golay filtering techniques within the broader context of FIR adaptive filter algorithms. The study primarily revolves around the implementation and analysis of Savitzky-Golay filtering techniques, which are widely recognized for their ability to preserve the signal's shape while effectively removing noise components. In addition to the Savitzky-Golay filter, several other FIR adaptive filter algorithms are evaluated and compared in terms of their denoising capabilities for adult ECG signals. These algorithms include Affine projection FIR adaptive filter (AP), Direct-form Normalized least-mean-square FIR adaptive filter (NLMS), and Sliding-window Recursive least-squares FIR adaptive filter (SWRLS).

1.1. Objective of this study

The primary aim of the research is to assess the effectiveness of the Savitzky-Golay filter in terms of filtering, denoising, and error compensation for ECG signals from adult individuals. Additionally, the article aims to compare the performance of various algorithms within the framework of this filtering technique.

2. Savitzky-Golay filter

The Savitzky-Golay filter is a digital signal processing technique used for smoothing and denoising time series data [8]. It operates by fitting a polynomial function to a small window of data points and using this polynomial to estimate the value at the center of the window. The filter is particularly useful for preserving the shape and features of the original signal while reducing noise.

The general equation for the Savitzky-Golay filter can be represented as follows:

$$y_{filtered} = \sum (c_i * y_i) \qquad (1)$$

where:

- $y_{filtered}$ represents the filtered output signal at a specific time point.

- y_i represents the input signal values within a given window.

- c_i represents the filter coefficients associated with the polynomial fit.

The key idea behind the Savitzky-Golay filter is to find the polynomial coefficients c_i that minimize the least-squares error between the polynomial fit and the original data points. This is achieved by solving a system of linear equations using a least-squares approach.

The specific form of the polynomial used in the filter is determined by two parameters: the window size (N) and the polynomial order (p). The window size represents the number of adjacent data points used for the polynomial fit, and the polynomial order determines the degree of the polynomial function.

The filter coefficients c_i can be computed using the following equation:

$$C = (X^T * X)^{-1} * X^T * Y \qquad (2)$$

where:

- C represents the vector of filter coefficients.

- X is a matrix containing powers of the independent variable (time) up to the desired polynomial order.

- Y is a vector containing the input signal values within the window.

Once the filter coefficients are obtained, they are used to perform the convolution operation, where the coefficients are applied to the input signal values to obtain the filtered output.

By adjusting the window size and polynomial order, the Savitzky-Golay filter can be tailored to specific applications, balancing the trade-off between noise reduction and preserving important signal features. It is widely used in various fields, including biomedical signal processing, where it has proven effective in denoising ECG signals and improving signal quality for accurate analysis and diagnosis [9].

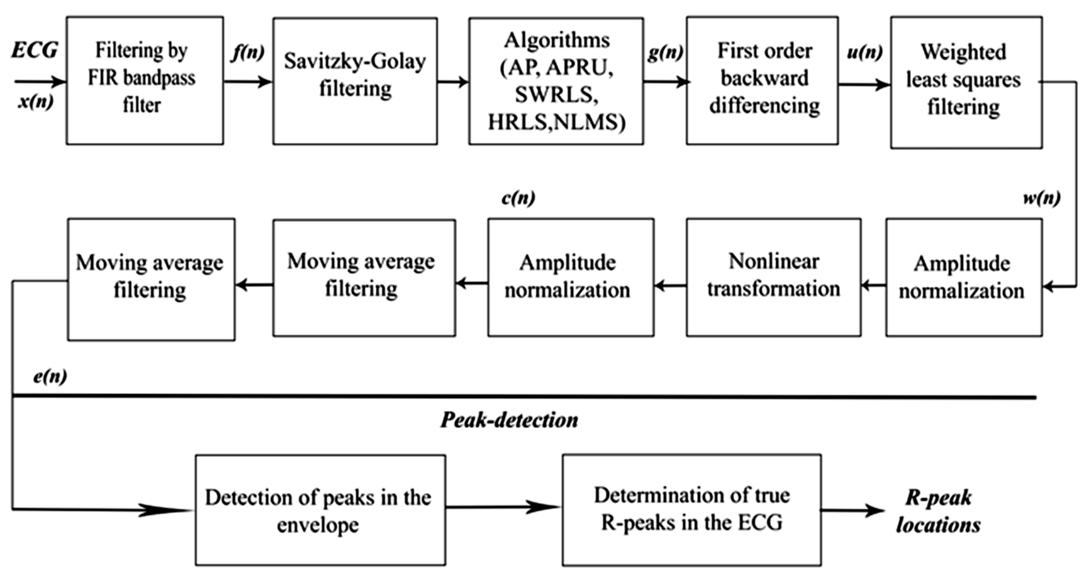

Figure 1. Block Diagram of Savitzky-Golay Filtering System

The process begins by applying a specific ECG signal to an FIR bandpass filter for initial filtration. Subsequently, the filtered signal undergoes Savitzky-Golay filtering. Following this, first-order backward differencing and weighted least squares filtering techniques are applied. The amplitude of the filtered signal is then normalized, and a non-linear transformation is performed. Average filtering is conducted thereafter. In the next step, the peaks of the signal are detected within the envelope. Finally, the true R-peaks in the ECG are determined [10].

3. Algorithms of Filtering ECG Signals

Various algorithms are utilized for filtering ECG signals to reduce noise and improve signal quality. One commonly used algorithm is the Savitzky-Golay filter [11], which applies a polynomial smoothing technique to preserve signal features while reducing noise.

3.1. Affine Projection Algorithm (AP)

The Affine Projection (AP) algorithm updates its filter coefficients based on the input signal and the desired signal [12]. The main equations of the AP algorithm can be expressed as follows:

Weight vector update equation:

$w(k+1) = w(k) + \mu * P(k) * u(k)$ (3)

Error signal calculation:

$e(k) = d(k) - y(k)$ (4)

Projection matrix update equation:

$P(k+1) = P(k) - (P(k) * u(k) * u(k)' * P(k)) / (\lambda + u(k)' * P(k) * u(k))$ (5)

where:

- $w(k)$ represents the filter coefficient vector at time step k.
- μ is the step size or adaptation parameter that controls the convergence speed of the algorithm.
- $P(k)$ is the projection matrix at time step k, which captures the correlation between the input signal and error.
- $u(k)$ represents the input signal vector at time step k.
- $d(k)$ represents the desired signal or the target signal at time step k.
- $y(k)$ denotes the filtered output signal at time step k.
- $e(k)$ represents the error signal, which is the difference between the desired signal and filtered output signal.
- λ is a regularization parameter that prevents matrix singularity.

These equations capture the iterative nature of the AP algorithm, where the filter coefficients and the projection matrix are updated at each time step based on the input signal, desired signal, and the error between them. The algorithm converges over time to minimize the error and adapt the filter to changes in the ECG signal.

3.2. Sliding-window Recursive least-squares FIR adaptive filter (SWRLS)

The Sliding-Window Recursive Least-Squares (SWRLS) FIR adaptive filter is a popular algorithm used for adaptive filtering in various applications, including ECG signal processing. It dynamically adjusts its filter coefficients based on the input signal and the desired signal within a sliding window. The main equations for the SWRLS algorithm can be expressed as follows [13]:

Weight vector update equation:

$w(k+1) = w(k) + (P(k) * u(k) * e(k)) / (\lambda + u(k)' * P(k) * u(k))$ (6)

Projection matrix update equation:

$P(k+1) = (1/\lambda) * (P(k) - ((P(k) * u(k) * u(k)' * P(k)) / (\lambda + u(k)' * P(k) * u(k))))$ (7)

Error signal calculation:

$e(k) = d(k) - y(k)$ (8)

where:

- $w(k)$ represents the filter coefficient vector at time step k.

- *P(k)* is the projection matrix at time step k, which captures the correlation between the input signal and the error within the sliding window.

- *u(k)* represents the input signal vector at time step k within the sliding window.

- *d(k)* represents the desired signal or the target signal at time step k.

- *y(k)* denotes the filtered output signal at time step k.

- *e(k)* represents the error signal, which is the difference between the desired signal and the filtered output signal.

- λ is a regularization parameter that prevents matrix singularity and controls the trade-off between convergence speed and stability.

The SWRLS algorithm iteratively updates the filter coefficients and the projection matrix within a sliding window. By considering a limited number of recent samples, the SWRLS algorithm adapts to changes in the ECG signal while maintaining computational efficiency. The updated filter coefficients provide an optimized response to the input signal and improve the quality of the filtered ECG signal.

3.3. Normalized least-mean-square FIR adaptive filter (NLMS)

The Normalized Least-Mean-Square (NLMS) FIR adaptive filter is a popular algorithm used for adaptive filtering in various signal processing applications, including ECG signal processing. It dynamically adjusts its filter coefficients based on the input signal and the desired signal while normalizing the step size to improve convergence. The main equation for the NLMS algorithm can be expressed as follows [14]:

Weight vector update equation:

$$w(k+1) = w(k) + (\mu / (\alpha + u(k)' * u(k))) * u(k) * e(k) \qquad (9)$$

where:

- *w(k)* represents the filter coefficient vector at time step k.

- μ is the step size or adaptation parameter that controls the convergence speed of the algorithm.

- α is a small positive constant added to the denominator to avoid division by zero and ensure stability.

- *u(k)* represents the input signal vector at time step k.

- *e(k)* represents the error signal, which is the difference between the desired signal and the filtered output signal.

The NLMS algorithm adjusts the filter coefficients at each time step based on the current input signal, the desired signal, and the error between them. The step size is normalized by the squared norm of the input signal to ensure stable and efficient convergence. This normalization factor helps to balance the adaptation rate across different input signal magnitudes and prevents the filter from becoming overly sensitive to large input variations.

By iteratively updating the filter coefficients using the NLMS algorithm, the adaptive filter can converge towards an optimal solution, reducing noise and improving the quality of the filtered ECG signal.

4. Methodology

The study employs the Matlab environment for conducting comprehensive experiments and evaluating the performance of each algorithm technique [15]. By analyzing and comparing the denoising outcomes achieved by these algorithms, the research provides valuable insights into their respective strengths and limitations in reducing noise from adult ECG signals. The findings of this study contribute to the advancement of ECG signal processing and offer crucial information for researchers and practitioners working with adult ECG data. The comparative analysis of different FIR adaptive filter algorithms sheds light on their denoising capabilities and their impact on the quality of recorded waveforms. By enhancing our understanding of these filter algorithms' effects, this research facilitates the development of improved techniques for analyzing abnormal heart rhythms and investigating the causes of chest pains based on accurate ECG measurements. The initial step involved generating an ECG signal specifically designed for adult individuals. Subsequently, the beat per minute (BPM) of this ECG signal was transformed into an appropriate input signal format for MATLAB [16]. Following this, the necessary MATLAB code was developed utilizing the Savitzky-Golay filter to effectively denoise the signal. Ultimately, the provided signal was successfully enhanced through this process.

5. Execution of denoising technique

The denoising technique is executed through the following successive steps:

(a) Creation of the heartbeat signal: The heartbeat signal for adult individuals is generated using an appropriate ECG rate. A matrix ratio is chosen, and random noise is multiplied with the selected signal to introduce noise into the person's heartbeat signal. The extracted heartbeat signal is obtained.

(b) Measurement of the electrocardiogram (ECG): The ECG is measured by applying a suitable filter and adding it to the selected signal. The maximum and minimum values of the measured ECG are determined.

(c) Measurement of implemented voltage: The implemented voltage is measured using the required code, and the maximum and minimum voltages are observed.

(d) Application of adaptive filter for noise removal: An adaptive filter is applied to recover the desired signal by eliminating unwanted noise. The maximum and minimum voltages are calculated.

For each type of filter, the following parameters were used:

- AP Filter: Step size of 0.1, Projection order of 4, and a covariance matrix of 0.13 resulted in the minimum error and higher efficiency.

- SWRLS Filter: Block length of 64 and a RLS forgetting factor of 0.99 were found to minimize the error and improve efficiency.

- NLMS Filter: Step size of 1 and a leakage factor of 50 were found to minimize the error and improve efficiency.

In each case, the measured signal, the error signal, and the percentage improvement of the signal were determined as evaluation metrics.

6. Numerical Outcomes

In this section, the generation of the heartbeat signal for adult individuals is carried out in a chronological manner. Subsequently, the specific voltages of these signals are measured and analyzed using adaptive noise cancellation techniques. The ECG signals used as the source for this analysis are obtained from the support database of Matlab biomedical tool library [17]. Finally, the proposed adaptive filter algorithms are evaluated using the extensive MATLAB simulation. The BPM (beats per minute) for adult individuals is set at 100. To convert this BPM value into the ECG rate suitable for MATLAB, a value of 1015 is obtained [18]. Figure 2 illustrates the heartbeat signal of adult individuals. Initially, the heartbeat signal is generated for an adult person using the appropriate ECG rate of 1015. A necessary matrix ratio is chosen, and random noise is multiplied with the corresponding fetal signal. Subsequently, the extracted heartbeat signal of adult individuals is obtained.

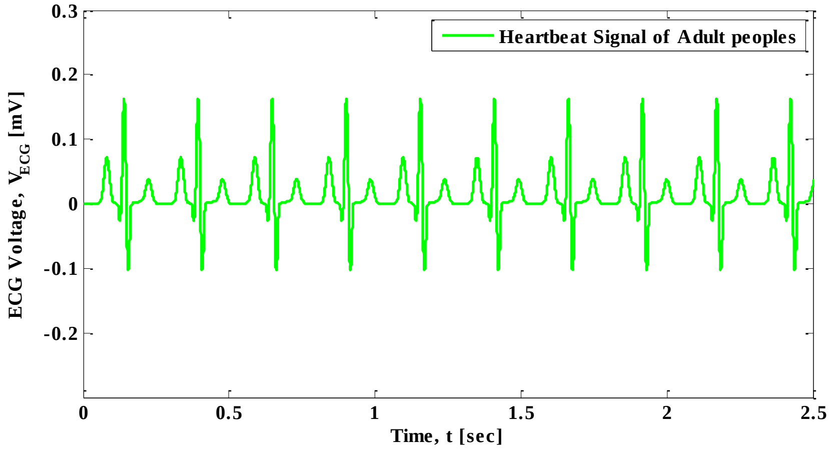

Figure 2. Normal heartbeat ECG signal of an adult person

In Figure 3, the measured signal for adult individuals is presented. The electrocardiogram (ECG) is obtained by applying an appropriate filter and combining it with the selected signal. The maximum value of the measured ECG is 0.2449 mV, while the minimum value is -0.1648 mV.

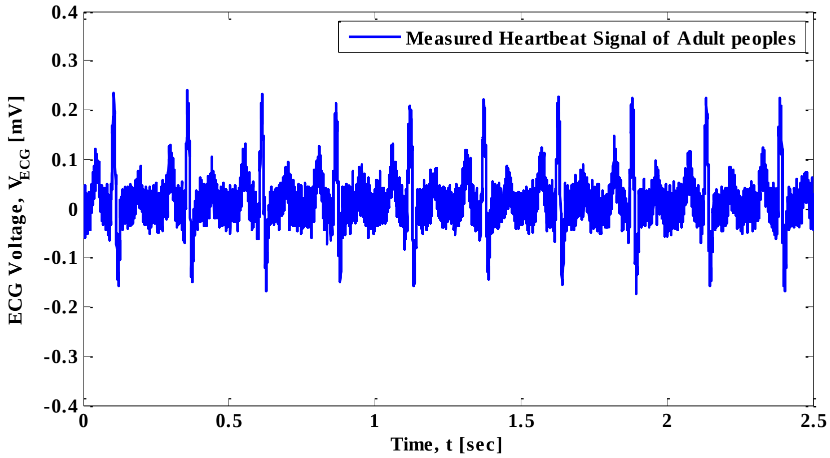

Figure 3. Measured heartbeat ECG signal of an adult person with noise

6.1. Cancellation of Noise using Affine Projection (AP) Algorithm Technique

The filtered ECG signal by the adaptive noise canceller utilizing the Affine Projection (AP) adaptive filter is shown in Figure 4. In the last stage of the denoising process, the adaptive filter is employed to recover the target signal by minimizing unwanted noise. The greatest voltage recorded after applying the adaptive filter is 0.2451 mV, while the minimum voltage measured is -0.1770 mV. The AP filter measured signal is 0.05365 mV, whereas the error signal is 0.004813 mV. As a result, the measured signal outperforms the preceding noisy signal by 91.03%. In this

Middle East Journal of Applied Science & Technology (MEJAST)
Volume 6, Issue 2, Pages 131-143, April-June 2023

case, the most efficient settings for achieving the lowest possible error were 0.1 step size, 4 projection order, and 0.13 covariance matrix.

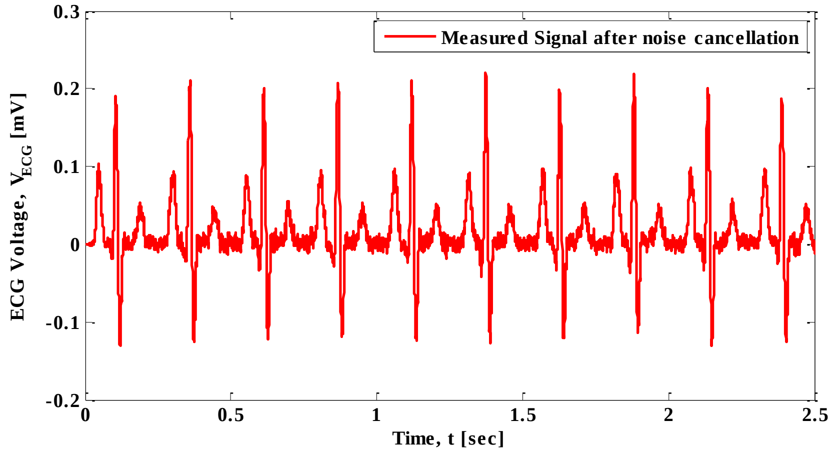

Figure 4. Measured ECG signal applying Affine Projection (AP) adaptive filter

6.2. Cancellation of Noise using Sliding-window RLS (SWRLS) Algorithm Technique

Figure 5 depicts the convergence of an adaptive noise canceller using the SWRLS adaptive filter. Finally, to recover the desired signal by removing the unwanted noise, an adaptive filter was applied, where the maximum voltage was measured 0.2491 mV and the minimum voltage was -0.1871 mV. In the case of using the SWRLS filter, the measured signal was 0.06701 mV and the error signal was 0.005647 mV, so the measured signal was 91.57% improved.

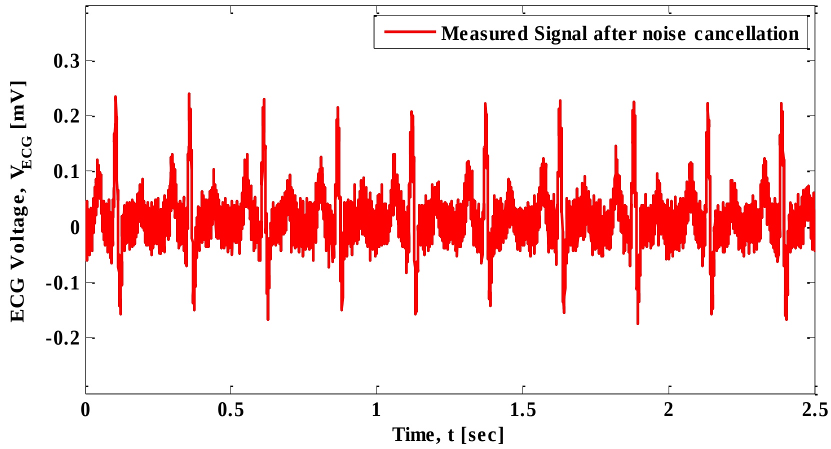

Figure 5. Measured ECG signal applying SWRLS adaptive filter

6.3. Cancellation of Noise using Normalized least-mean-square (NLMS) Algorithm Technique

Figure 6 depicts the convergence of an adaptive noise canceller using the NLMS adaptive filter. Finally, an adaptive filter was used to recover the required signal by reducing the undesirable noise, with a maximum voltage of 0.2513 mV and a minimum value of -0.1769 mV. In the instance of the NLMS filter, the measured signal was 0.2159 mV and the error signal was 0.04227 mV. As a result, the measured signal was 80.42% better. In this case, 1 was chosen as the step size, and 50 was found to be the most efficient leakage factor with the least amount of inaccuracy.

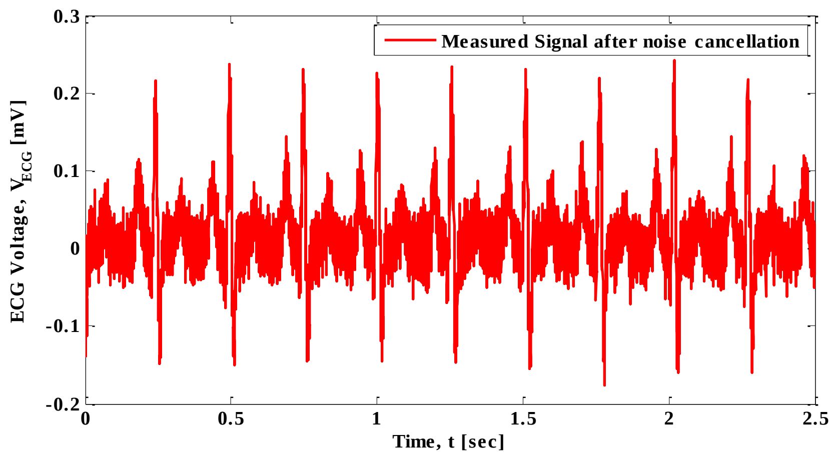

Figure 6. Measured ECG signal applying NLMS adaptive filter

Table 1. Performance evaluation of several types of filtering algorithms

Algorithm Technique	**Parameters**	**Measured Signal,** $V_{measured}$ **(mV)**	**Error Signal,** V_{error} **(mV)**	**Error (%),** $e(\%)=\frac{V_{error}}{V_{measured}}\times 100\%$	**Noise Reduction (%),** $N_r(\%)=\frac{V_{measured}-V_{error}}{V_{measured}}\times 100\%$
AP	μ=0.1 p_o=4 offset=0.13	0.053650	0.004813	8.97%	91.03%
SWRLS	λ=0.99 N=64	0.067010	0.005647	8.43%	91.57%
NLMS	μ=1 offset=50	0.21590	0.04227	19.58%	80.42%

7. Conclusion and Future Recommendation

In conclusion, this study focused on denoising adult electrocardiogram (ECG) signals using various FIR adaptive filter algorithms. It addressed the challenges posed by noise sources like power line interference, external electromagnetic fields, random body movements, and respiration, which can affect ECG measurement accuracy. The study evaluated and compared the denoising capabilities of different algorithm techniques, including Affine projection FIR adaptive filter (AP), Direct-form Normalized least-mean-square FIR adaptive filter (NLMS), and Sliding-window Recursive least-squares FIR adaptive filter (SWRLS). Experiments conducted in Matlab provided insights into the effectiveness of FIR adaptive filter algorithms in reducing noise from ECG signals. Results demonstrated the comparative performance of the techniques and their impact on recorded waveform quality. This research enhances the understanding of FIR adaptive filter algorithms' potential applications in ECG signal processing. The findings contribute to improved techniques for analyzing abnormal heart rhythms and investigating chest pain causes based on accurate ECG measurements. Overall, this study advances the field of ECG signal denoising and provides valuable information for researchers and practitioners working with adult ECG data. It confirms the effectiveness of FIR adaptive filter algorithms, specifically AP, NLMS, and SWRLS, in reducing noise from adult ECG signals, highlighting their potential to enhance ECG measurement accuracy. Future research recommendations involve investigating hybrid methods that combine various denoising algorithms or include machine learning techniques to improve the denoising performance of adult ECG signals. Furthermore, exploring the possibility of using FIR adaptive filter algorithms in real-time during live ECG monitoring might increase the clinical value of ECG signal processing. Conducting robustness study with a broad set of noise sources and situations can aid in identifying limits and improving algorithm performance in real-world scenarios. Collaboration with healthcare experts for clinical validation and the use of denoising algorithms on real patient ECG data might be used to evaluate their influence on diagnosis accuracy. Furthermore, applying the findings of the study to denoise other biological signals, such as blood pressure or respiratory waveforms, can help to improve signal quality in a variety of medical monitoring domains. Researchers can develop ECG signal denoising by addressing these future prospects, resulting in increased diagnosis accuracy and patient care.

Declarations

Source of Funding

This study did not receive any grant from funding agencies in the public or not-for-profit sectors.

Competing Interests Statement

The authors have declared no competing interests.

Consent for Publication

The authors declare that they consented to the publication of this study.

Authors' Contribution

All authors took part in literature review, research, and manuscript writing equally.

Acknowledgements

Authors are thankful to the Management of Rangpur Metropolitan Diagnostic & Consultation Center, Sakina Mazid Memorial Diagnostic Center and World University of Bangladesh for their cooperation and support.

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