Denoising of ECG signal for Heart rate Prediction

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***Abstract*—The increasing importance of accurate cardiac diagnostics has led to a growing need for effective denoising techniques in processing Electrocardiogram (ECG) signals. Digital Signal Processing (DSP) emerges as a powerful tool in addressing the challenge of noise reduction, with the Discrete Fourier Transform (DFT) offering a robust method for frequency analysis. Our approach focuses on leveraging DFT to transform ECG signals into the frequency domain, facilitating a detailed examination of their spectral components. Filters are strategically employed to selectively eliminate noise frequencies, ensuring that essential features of the ECG waveform remain intact. The proposed methodology involves a comprehensive preprocessing step to prepare raw ECG signals for frequency domain analysis. Through the application of DFT, the frequency representation of the signal is obtained, providing insights into the underlying components contributing to the noise. Carefully designed filters are then applied to target and attenuate specific noise frequencies, resulting in a denoised ECG signal of improved quality. The denoising process aims to enhance the interpretability of ECG signals, supporting accurate diagnosis by healthcare professionals. The outcomes of our experiments underscore the effectiveness of the proposed approach, positioning it as a valuable contribution to the field of ECG signal processing for cardiac diagnostics.**

***Index Terms*—ECG signal, Discrete Fourier Transform (DFT), FFT, IIR filters, FIR filters.**

I. INTRODUCTION

In the realm of medical diagnostics, the Electrocardiogram (ECG) serves as a fundamental tool for monitoring and evaluating the electrical activity of the heart. Over the past decades, the significance of accurate ECG signal analysis has grown exponentially, with advancements in technology continually shaping the landscape of cardiac diagnostics. Historically, ECG signals have been susceptible to various forms of noise, stemming from sources such as electrode contact issues, muscle artifacts, and external interferences.Early attempts at mitigating these challenges primarily relied on analog filtering techniques, which, while providing some improvement, often fell short in addressing the complexities of modern healthcare demands. With the advent of Digital Signal Processing (DSP), a paradigm shift occurred in the approach to ECG signal enhancement. Recent years have witnessed an increased reliance on advanced DSP techniques, offering a more sophisticated and nuanced means of tackling noise reduction in ECG signals.This paper delves into the evolution of ECG signal denoising methodologies, tracing the historical challenges and solutions that paved the way for contemporary approaches.

Analogous to the evolution of technology, the transition from analog to digital methods represents a pivotal moment in the quest for enhanced diagnostic accuracy. The integration of the Discrete Fourier Transform (DFT) into ECG signal processing has emerged as a key strategy, providing a comprehensive frequency domain analysis that enables a deeper understanding of the signal's composition.In the present landscape, our research stands at the intersection of historical challenges and cutting-edge solutions. By harnessing the power of DFT and judiciously applying digital filters, we aim to present a robust and effective approach to ECG signal denoising. The subsequent sections detail our methodology, experimentation, and results, highlighting the potential impact of our proposed technique on the field of cardiac diagnostics.

II. LITERATURE SURVEY

In the first paper, They have presented a novel ECG denoising method using wavelet transform coefficients and thresholding, which demonstrates improved results over Donoho's method when tested with MATLAB. It emphasizes the importance of ECG signals in diagnosing heart conditions and suggests that wavelet transform is efficient for non-stationary signal processing like ECG. The methodology involves adding noise to the original ECG signal, decomposing signals with wavelet transform, applying a threshold to minimize error, and then reconstructing

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the signal. Experimental results show that the proposed thresholding method yields a higher Signal to Noise Ratio (SNR) and lower Percentage Root mean square Difference (PRD) than Donoho's thresholding, indicating better preservation of ECG waveforms. The paper concludes that the wavelet transform is effective for processing non-stationary signals such as ECG, and the new thresholding approach provides a better quality denoised signal.

In the second paper They evaluated five common ECG denoising methods: discrete wavelet transform (universal and local thresholding), adaptive filters (LMS and RLS), and Savitzky-Golay filtering, using real ECG signals contaminated with different noise levels. The discrete wavelet transform proved useful in non-stationary signal processing, with the 'NeighBlock' method allowing for local noise level adaptation, offering slight improvements over 'SureShrink' which applies a universal threshold. Adaptive filters adjust their parameters iteratively to minimize error, with LMS being simpler and RLS being more computationally intensive but faster in convergence. Savitzky-Golay filtering uses local least-squares polynomial approximation for smoothing and was found to be effective but introduced slight distortions in the absence of noise. The comparison across different SNR levels showed that 'NeighBlock' wavelet denoising performed best overall, but RLS and Savitzky-Golay had advantages in mid-range SNRs, with the possibility of further improvements when combined with low-pass filtering in specific SNR ranges.

In The Third paper paper ,It discusses the application of the Recursive Least Squares (RLS) algorithm for denoising ECG signals, addressing issues such as power line interference, baseline wander, and muscle artifacts.It highlights the challenge of separating the desired ECG signal from various types of noise and suggests that adaptive filters, particularly the RLS algorithm, are suitable for this purpose due to their ability to preserve low-frequency components and fine features of ECG.The authors present a simulation-based comparison of the RLS algorithm with traditional LMS (Least Mean Squares) methods, showing that RLS converges faster and has a better signal-to-noise ratio.A variety of ECG signal morphologies from the MIT-BIH arrhythmia database were used for validation, indicating the RLS algorithm's effectiveness in clinical situations.The paper concludes that the RLS algorithm provides an efficient noise cancellation method for ECG signals, offering faster convergence and lower computational complexity compared to LMS-based methods.

In The Fourth paper They have proposed a hybrid denoising technique combining Daubechies wavelet decomposition with Butterworth or Chebyshev filters to remove baseline wander from ECG signals. Utilizing MATLAB, the authors add generated noise to real ECG signals from a non-invasive fetal electrocardiogram database to evaluate the denoising performance of the proposed method.Both filters are compared in terms of minimum mean squared error (MSE), signal to interference ratio (SIR), and peak signal to noise ratio (PSNR), with the results showing very close performance between the two.The study finds that the Butterworth filter has a better balance between smoothness and accuracy than the Chebyshev filter.The conclusion suggests that while both filters effectively denoise ECG signals, further enhancements could be achieved by combining wavelet transform with other techniques such as the Savitzky-Golay filter.

III. Methodology

A. Data Collection and Preprocessing

Dataset Source:

The electrocardiogram (ECG) data was obtained from physionet.org, consisting of 5000 data points recorded over a duration of 10 seconds.

Signal Characteristics:

Amplitude Range: The ECG signals exhibit amplitudes ranging from -100 to 250 V. Sampling Frequency: The data was sampled at a rate of 500 Hz. Frequency Range: The signal spans frequencies from 0 to 250 Hz.

B. Discrete Fourier Transform(DFT)

The Discrete Fourier Transform (DFT) is a fundamental tool in signal processing that transforms a discrete signal from its time-domain representation to its frequency-domain representation. In the context of ECG signal processing, DFT is applied to analyze the frequency components present in the signal. Mathematically, the DFT is expressed as a sum of complex exponential functions, providing information about the amplitude and phase of various frequency components within the signal. The fast computation of DFT is facilitated by the Fast Fourier Transform (FFT) algorithm, which significantly reduces the computational burden.

The DFT Equation is given by X[k] = $\sum_{n=0}^{N-1} x[n] \cdot e^{-j\left(\frac{2\pi}{N}\right)kn}$

C. Fast Fourier Transform(FFT)

FFT is an efficient algorithm for computing the DFT and is widely utilized in signal processing due to its computational speed. It breaks down the DFT computation into smaller sub-problems, resulting in a significant reduction in the number of arithmetic operations required. FFT is particularly relevant in real-time applications, making it a key component in the analysis of ECG signals. Its efficiency is crucial for processing large datasets, allowing for faster and more practical implementation of frequency domain analysis.

D. DIT - Fast Fourier Transform(FFT)

In the DIT FFT algorithm, the time-domain sequence is recursively divided into smaller sequences, leading to a butterfly structure in the computation. The DIT approach starts with the entire sequence and recursively breaks it down into smaller parts. The twiddle factors (complex exponential terms) are applied at each stage of the computation. The DIT FFT can be represented mathematically as follows:

X(k) = $\sum_{n=0}^{N-1} x(n) \cdot W_N^{kn}$

E. DIF - Fast Fourier Transform(FFT)

Conversely, in the DIF FFT algorithm, the frequency-domain sequence is divided, and the computation is performed in a bottom-up manner. The DIF approach starts with the smallest frequency components and builds up to the entire sequence. The twiddle factors are applied after combining the results of smaller computations. Mathematically, the DIF FFT can be expressed as:

X(k) = $\sum_{n=0}^{N-1} x(n) \cdot W_N^{kn}$

F. Infinite Impulse Response(IIR) Filters

IIR filters are a class of digital filters characterized by feedback in their implementation. In ECG signal processing, IIR filters are employed for their ability to achieve a desired frequency response with fewer coefficients, making them computationally efficient. These filters have recursive structures, allowing for feedback of past output values, which can result in more compact designs. IIR filters are used in applications where a trade-off between computational complexity and frequency response accuracy is acceptable.

1) Butterworth Filter: The Butterworth filter is known for its maximally flat frequency response in the passband. In other words, it provides a smooth and monotonic roll-off from the passband to the stopband without any ripples in the passband. The Butterworth filter is characterized by a flat frequency response in the passband, making it suitable for applications where a consistent gain is desired over a wide range of frequencies.

2) Chebyshev Filter: The Chebyshev filter, on the other hand, is designed to provide a steeper roll-off in the stopband at the expense of allowing ripples in the passband. This characteristic makes Chebyshev filters suitable for applications where a faster transition between the passband and stopband is required. Chebyshev filters come in two types: Type I (or Chebyshev Type I) has ripple in the passband, and Type II (or Chebyshev Type II) has ripple in the stopband.

G. Finite Impulse Response

FIR filters differ from IIR filters in that they do not use feedback in their implementation. In the context of ECG signal processing, FIR filters are often preferred for their stability and linear phase characteristics. FIR filters are characterized by a finite duration of their impulse response, which simplifies their design and analysis. Windowing is a common technique used with FIR filters to mitigate the effects of spectral leakage, where the signal appears to spread across multiple frequency bins. Popular window functions include the Hamming, Hanning, and Blackman windows, each influencing the filter's frequency response and sidelobe behavior.

H. Windowing Methods for FIR Filters

Windowing is a crucial aspect of FIR filter design, and different window functions impact the performance of the filter in various ways. Common window functions include:

1) Hamming Window: The Hamming window is widely used due to its balance between main lobe width and sidelobe suppression. It minimizes spectral leakage while offering a relatively narrow main lobe.

2) Hanning Window: Similar to the Hamming window, the Hanning window is effective in reducing sidelobes. It provides a smoother transition from the passband to the stopband and is often preferred in applications where a wider main lobe is acceptable.

3) Blackman Window: The Blackman window offers improved sidelobe suppression compared to Hamming and Hanning windows but has a wider main lobe. It is chosen when stringent requirements for sidelobe attenuation are necessary.

4) Bartlett Window: The Bartlett window, resembling a triangular shape, is useful in signal processing for its tapering effect towards the edges. It is often preferred when a compromise between the simplicity of a rectangular window and improved side-lobe suppression is desired. The window function is defined by gradually reducing the amplitude towards the edges.

5) Rectangular Window: The Rectangular window, also known as the boxcar window, is the simplest window function, characterized by a constant value within its length and zero outside. Although straightforward, it suffers from poor side-lobe suppression, leading to spectral leakage in the frequency domain. It is rarely used alone but finds application in scenarios where a sharp main lobe is crucial, and side-lobe effects can be tolerated.

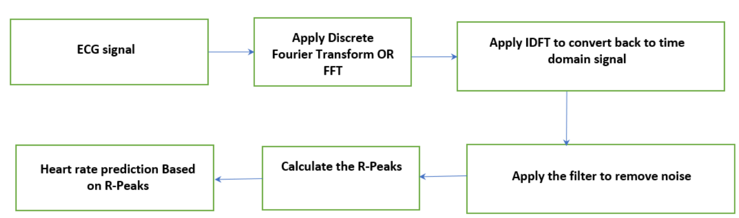

Fig. 1. Function Block Diagram

IV. Results and Discussions

In our project, we identified the precise R-peaks and heart rate using a bandpass filter with various window functions. We observed that all window techniques successfully extracted the exact R-peak. When addressing noise concerns, the bandpass filter with a Blackmann window stood out, excelling in eliminating DC component noise and proving to be more effective than other window techniques.Before filtering the heart rate was 124 bpm. After filtering the the calculated heart rate came to be 67 bpm

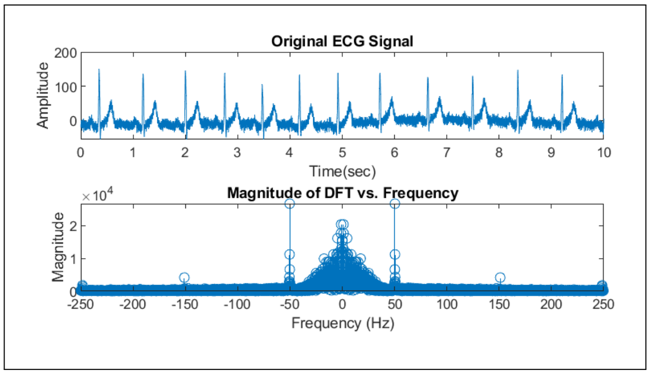

Fig. 2. DFT Output

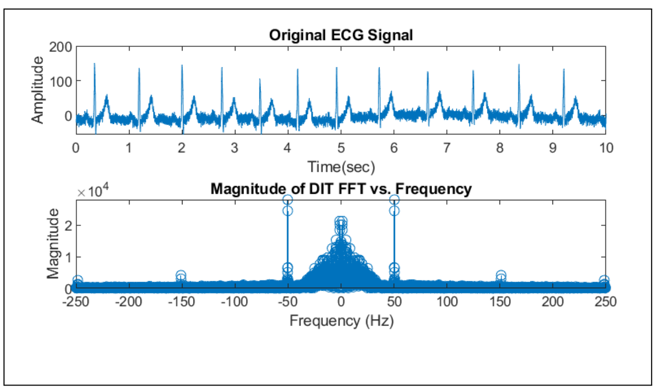

Fig. 3. DIT FFT Output

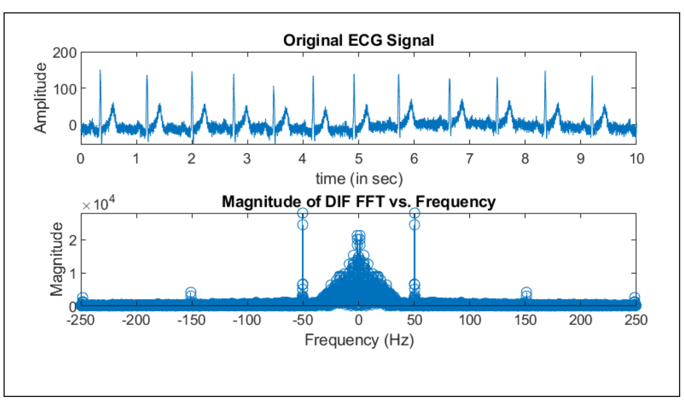

Fig. 4. DIF FFT Output

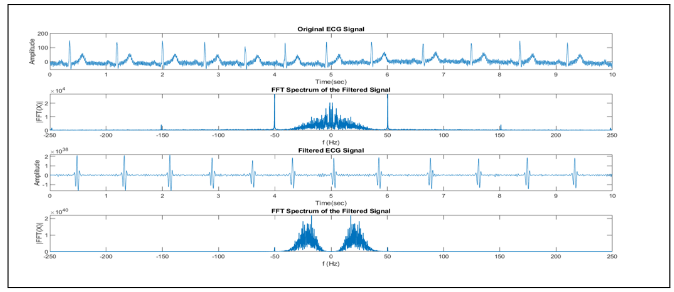

Fig. 5. IIR Butterworth Filter Output

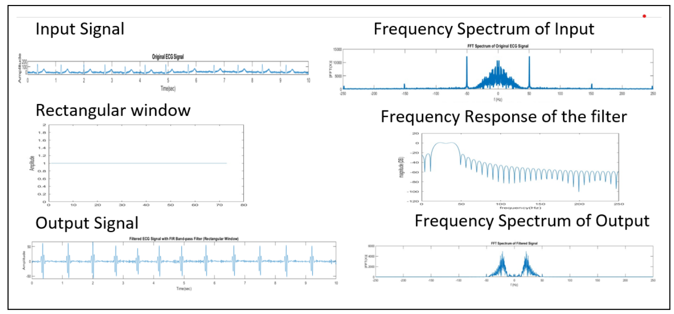

Fig. 6. FIR Rectangular Window Output

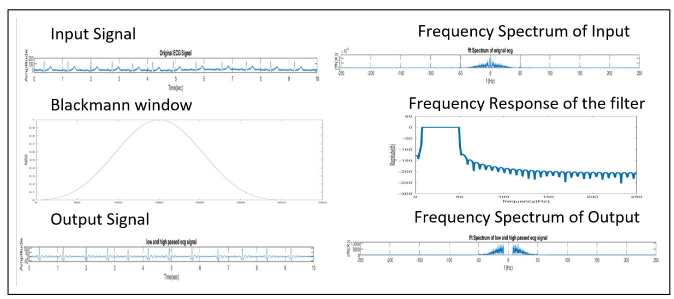

Fig. 7. FIR Blackmaan Window Output

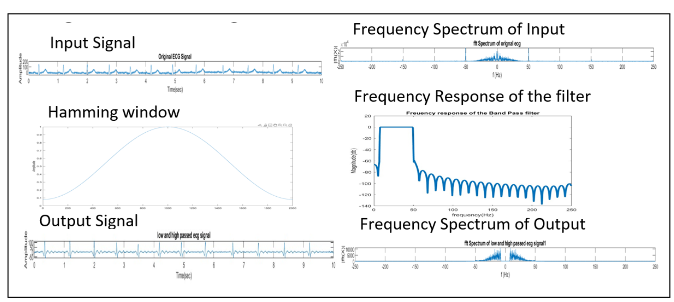

Fig. 8. FIR Hamming Window Output

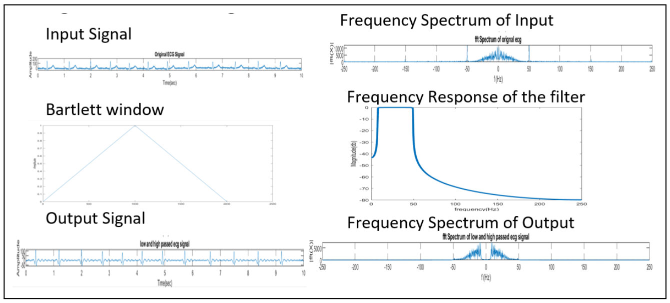

Fig. 9. FIR Bartlett Window Output

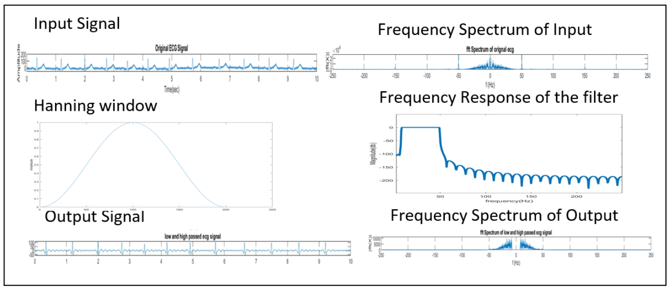

Fig. 10. FIR Hanning Window Output

This study employs a multifaceted approach to enhance the diagnostic quality of electrocardiogram (ECG) signals. Figure 1 showcases the Discrete Fourier Transform (DFT) output, providing a detailed frequency spectrum that aids in identifying noise frequencies and unraveling the underlying components of the original ECG signal. Figures 2 and 3 present the outcomes of Decimation In Time Fast Fourier Transform (DIT FFT) and Decimation In Frequency Fast Fourier Transform (DIF FFT) algorithms, respectively, offering distinct perspectives on frequency analysis and enriching our understanding of the signal's frequency distribution. Figure 4 demonstrates the impact of an Infinite Impulse Response (IIR) Butterworth filter, effectively isolating specific frequency bands associated with key cardiac components and enhancing the interpretability of the QRS complex. Figures 5 to 7 delve into Finite Impulse Response (FIR) filters with various windowing methods, emphasizing their capability to suppress noise while preserving critical features like the QRS complex. Collectively, these visualizations contribute to a comprehensive signal processing framework, advancing the accuracy of cardiac diagnostics by highlighting key frequency components and facilitating noise reduction.

V. Conclusions

In conclusion, this study presents a comprehensive signal processing framework aimed at enhancing the interpretability and diagnostic value of electrocardiogram (ECG) signals. Leveraging techniques such as the Discrete Fourier Transform (DFT), Decimation In Time Fast Fourier Transform (DIT FFT), and Decimation In Frequency Fast Fourier Transform (DIF FFT), we gained profound insights into the frequency domain characteristics of the ECG signal. The application of an Infinite Impulse Response (IIR) Butterworth filter demonstrated effective noise reduction, particularly in isolating specific frequency bands associated with critical cardiac components, prominently the QRS complex.

The incorporation of Finite Impulse Response (FIR) filters employing diverse windowing methods, including Rectangular, Bartlett, Hamming, Hanning, and Blackman, showcased their collective efficacy in suppressing noise while preserving essential features of the ECG waveform. These filtering methods play a pivotal role in improving the accuracy of cardiac diagnostics by emphasizing key frequency components and facilitating a clearer representation of the underlying cardiac activity.

The results of our experiments underscore the effectiveness of the proposed signal processing techniques in enhancing the diagnostic quality of ECG signals. The visualizations provided in this study serve as a valuable resource for healthcare professionals and researchers, offering a nuanced understanding of signal characteristics and noise reduction strategies. As we navigate the intricate landscape of cardiac diagnostics, this research contributes to the ongoing pursuit of accurate and reliable interpretation of ECG signals for informed clinical decision-making. The findings presented here not only advance the field of ECG signal processing but also lay the groundwork for further exploration and refinement of signal processing methodologies in the realm of cardiovascular health.

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