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A STATISTICAL COMPARISON OF FIR KAISER WINDOW AND IIR BUTTERWORTH FILTERS IN ECG SIGNAL PRE-PROCESSING

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Abstract: The work in this paper investigates the efficiency of FIR Kaiser Window and IIR Butterworth filters in ECG signal processing, which have been utilized to filter out noise components. For this purpose, numerical simulations of statistical parameters, including signal-to-noise ratio, signal strength, and power retained for both filter designs, are measured and compared. This comparison aims to unveil the strengths and limitations of each filter type, crucial for decision-making in clinical research, particularly in detecting subtle abnormalities within the ECG waveforms. MATLAB simulation tools are used to implement these filtering methods on the ECG data collected by the MIT-BIH ECG Arrhythmia database.

Index Terms: **Discrete Wavelet Transform, ECG Signal Processing, Finite Impulse Response, MATLAB, Windowing Technique**

I. INTRODUCTION

The Electrocardiogram (ECG) serves as a pivotal diagnostic tool, offering insights into the heart's electrical activity. It gives complete information of each event taking place in one cardiac cycle which can be graphically represented using ECG waveform. **Fig.1** represents various components of ECG signal including the P wave, QRS complex, S wave, and T wave, intervals and segments [1].

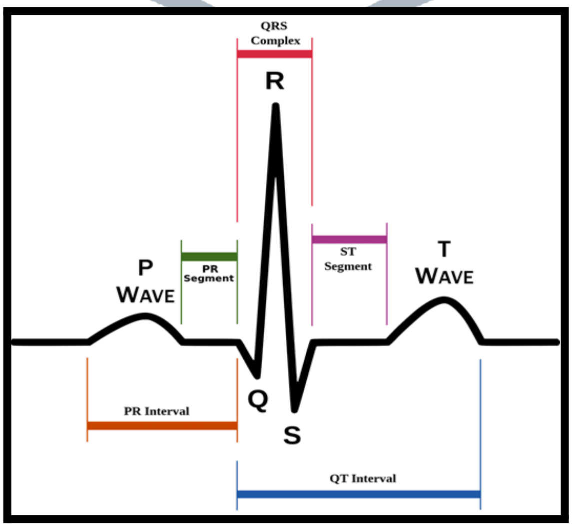

Figure 1: General waveform of an ECG signal

The fidelity of raw ECG recordings is often compromised by noise and signal complexity. Advanced research techniques are used to filter out noise components and delineate the useful signal features. However, there are various challenges in front of the researchers, which are also reported in literature, in the implementation of filtering techniques due to the time-varying behavior of low-frequency and low-amplitude ECG signals.

1.1 ECG Preprocessing Techniques

ECG preprocessing is the noise removal stage used to filter out various low and high frequency noise components and remove artifacts [2]. This preprocessing is an essential step to enhance the quality and utility of ECG signals for clinical diagnosis and research. **Fig.2** depicts the steps in ECG Signal Processing: preprocessing eliminates noise, feature extraction identifies ECG components, and classification discerns classes based on input features.

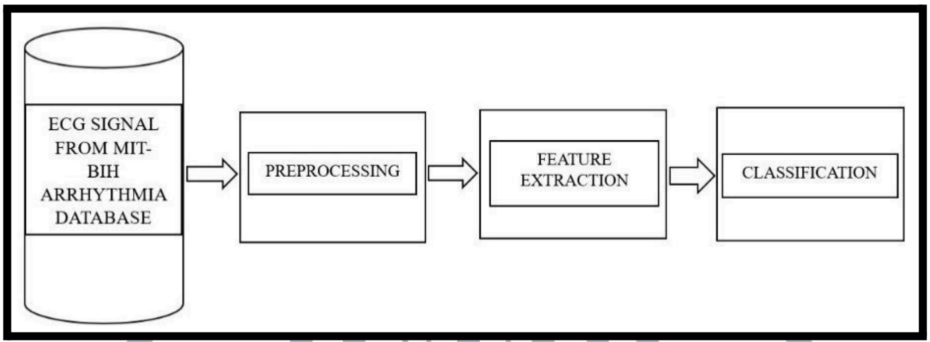

Figure 2: Block level diagram of signal processing

1.2 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is renowned for its ability to break down signals into distinct frequency components across various scales through filtering and downsampling. DWT outperforms Fourier-based techniques in handling non-stationary signals effectively, making it indispensable in Electrocardiogram (ECG) analysis due to the intricate nature of cardiac signals [3]. Each DWT level consists of high-pass and low-pass filters, which utilize characteristics of either Infinite Impulse Response (IIR) or Finite Impulse Response (FIR) filters, depending on the features extracted or highlighted for the application. The DWT scalogram provides a visual representation of time-frequency characteristics, offering a simultaneous depiction of both domains with its symmetrical attributes resembling ECG waveforms, ensures balanced representation across time and frequency domains, enhancing accuracy and noise suppression. **Fig.3** depicts the methodology that yields approximation and detail coefficients, capturing both coarse and fine-scale features

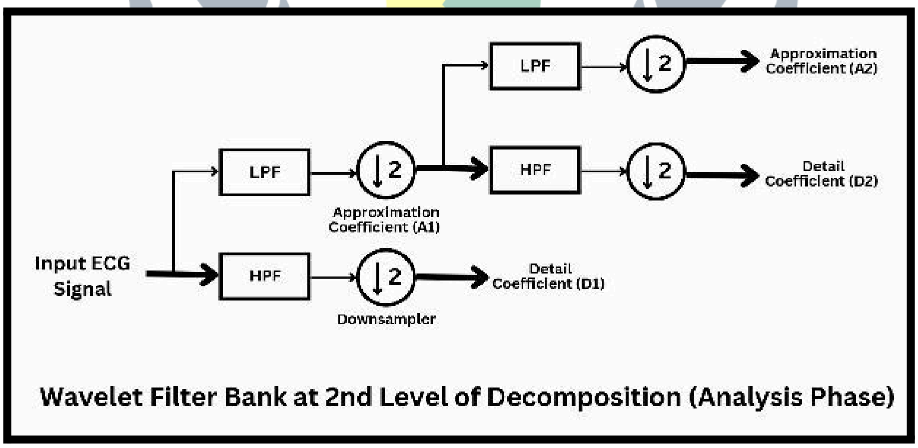

Figure 3: DWT filter banks

1.2.1 FIR Kaiser Window Filter:

The Kaiser Window method is employed to design the filter coefficients using the windowing method, influencing the frequency response [4].

$$Y(n) = \sum_{k=0}^{M} h(k) \bullet X(n-k) \tag{1.1}$$

The above equation represents the convolution operation, where $Y(n)$ is the filtered signal, $X(n)$ is the input signal, and $h(k)$ are the FIR filter coefficients.

1.2.2 IIR Butterworth Filter:

IIR filters, characterized by an infinite-duration impulse response, use both current and past input samples to calculate the output. It provides a maximally flat frequency response in the passband.

$$Y(n) = \sum_{k=0}^{N} b(k) \bullet X(n-k) - \sum_{k-1}^{M} a(k) \bullet Y(n-k) \tag{1.2}$$

The equation characterizes the recursive nature of IIR filtering. Here $Y(n)$ is the filtered signal, $X(n)$ is the input signal, and $b(k)$ and $a(k)$ are the filter coefficients [5].

1.3 Statistical Parameters

1.3.1 Signal-to-Noise Ratio (SNR)

SNR quantifies the ratio of the power of the ECG signal to the power of noise. A higher SNR indicates a clearer signal [6].

$$SNR = 10.\, log_{10} \frac{Power\ of\ Signal}{Power\ of\ Noise} \quad (1.3)$$

1.3.2 Mean Square Error (MSE)

MSE measures the average squared difference between the original and filtered signals. Lower MSE values indicate better filtering performance [7].

$$\text{MSE}= \frac{1}{N}\sum_{i-1}^{N}(X(i) - Y(i))^2 \quad (1.4)$$

1.3.3 Signal Strength

Signal strength, commonly known as signal power or magnitude, signifies the intensity or amplitude of a signal. It is usually measured by the square of the signal's amplitude. [8].

$$\text{Signal Strength} = |s(t)|^2 \quad (1.5)$$

1.3.4 Power Retained

Power retained measures the contribution of each level of DWT decomposition to the total power of the ECG signal, aiding in understanding signal components at different scales [9].

$$\text{Power Retained} = \frac{Power\ of\ Signal\ at\ a\ Level}{Total\ Power\ of\ Signal} \quad (1.6)$$

II. METHODOLOGY

Figure 4 illustrates the step-by-step process involved in implementing the Discrete Wavelet Transform (DWT) methodology for processing ECG signals. It encompasses signal preprocessing, DWT decomposition, analysis of signal quality metrics and concluding stages.

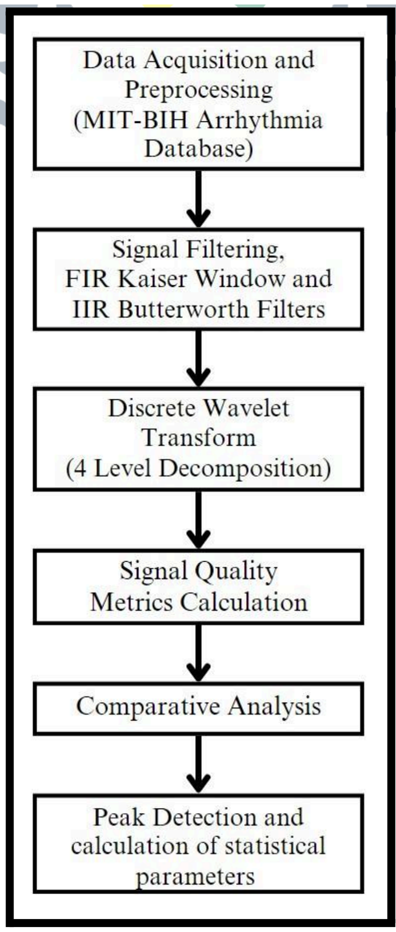

Figure 4. Workflow diagram of DWT methodology in ECG signal processing

III. RESULTS AND DISCUSSION

The work in this paper used ECG signals downloaded from the Physionet Massachusetts Institute of Technology - Beth Israel Hospital (MIT-BIH) arrhythmia database [10]. Employing the Symlet4 wavelet for DWT signal decomposition, precise coefficient extraction at each level is achieved. The analysis revealed processed ECG signals that exhibited minimal noise using measured value of statistical parameters, indicating the efficacy of the applied DWT methodology [11].

The implementation of FIR Kaiser Window is shown in Algorithm 1.

Algorithm 1: Designing of FIR filter

fc_low, fc_high = 32, 4.8 # **Define cutoff frequencies**
window_hp = kaiser(N_hp+1, beta_hp) / sum(kaiser(N_hp+1, beta_hp)) #**design high-pass FIR filter**
b_hp = fir1(N_hp, fc_hp / (Fs/2), 'high', window_hp)
ECGsignal_filtered = filtfilt(b_hp, 1, ECGsignal_filtered) # **Apply high-pass FIR filter to the ECG signal**

Algorithm 2: Calculation of SNR, MSE, Power Retained, Signal-to-Interference Ratio and Signal Strength

SNR_dB = 10 * log10(power_signal / power_noise); **% Calculate SNR in decibels (dB)**
MSE = mean((ECGsignal_actual - ECGsignal_estimated).^2); **% Calculate Mean Squared Error (MSE)**
power_retained = (power_filtered / power_original) * 100; **% Calculate Power Retained as percentage**
signal_strength = abs(ECGsignal_filtered).^2; **% Calculate Signal Strength**

The resultant ECG signal waveform, with the measured values of all mentioned parameters, is shown in **Fig.5**.

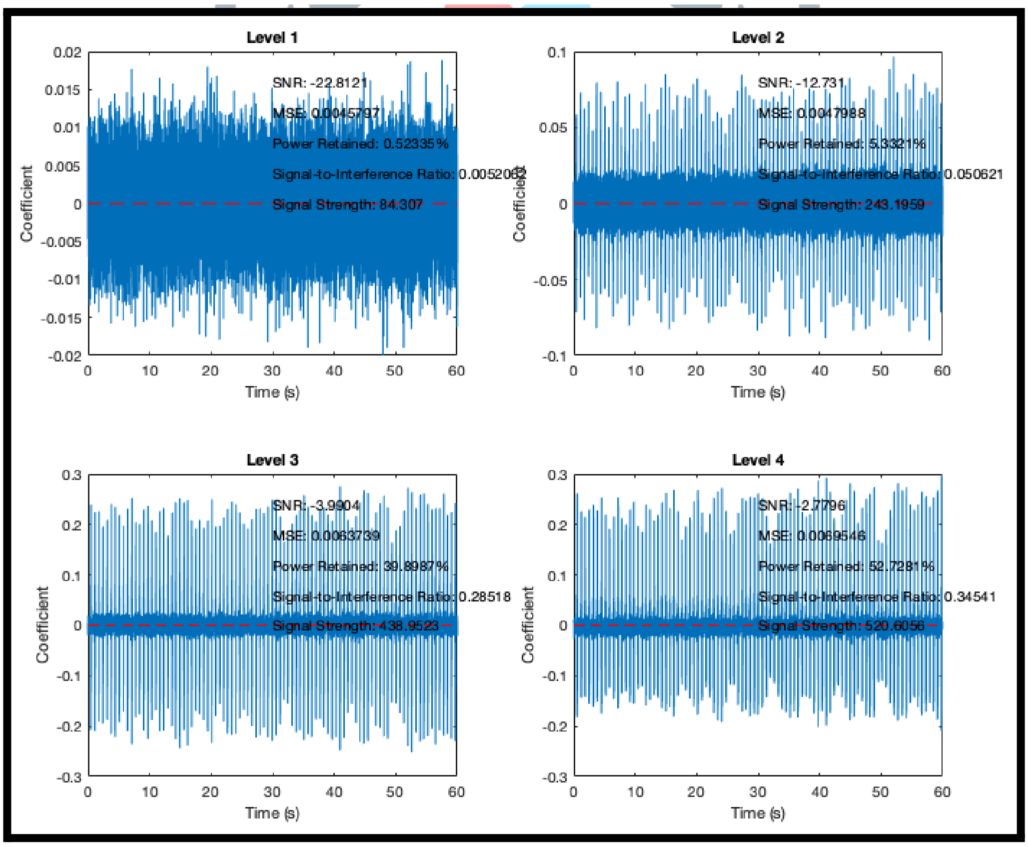

Figure 5. FIR kaiser window

The implementation of IIR high-pass Butterworth filter and IIR Notch filter is shown in Algorithms 3 and 4, respectively.

Algorithm 3: Designing of High Pass IIR Butterworth Filter

fc_highpass = 0.5 # **Define the cutoff frequency for the high-pass filter**
[b_highpass, a_highpass] = butter(2, fc_highpass / (Fs/2), 'high') # **Design a 2nd-order high-pass Butterworth filter**ECGsignal_filtered = filter(b_highpass, a_highpass, ECGsignal) # **Apply high-pass filter to ECG signal**

Algorithm 4: Designing_IIR_NotchFilter

fc_notch = 60;
[b_notch, a_notch] = iirnotch(fc_notch / (Fs/2), fc_notch / (Fs/2) / 10); # **Design an IIR notch filter**

ECGsignal_filtered = filter(b_notch, a_notch, ECGsignal_filtered); **# Apply notch filter to ECG signal**

The resultant ECG signal waveforms, with the measured values of all mentioned parameters, are shown in **Fig.6**:

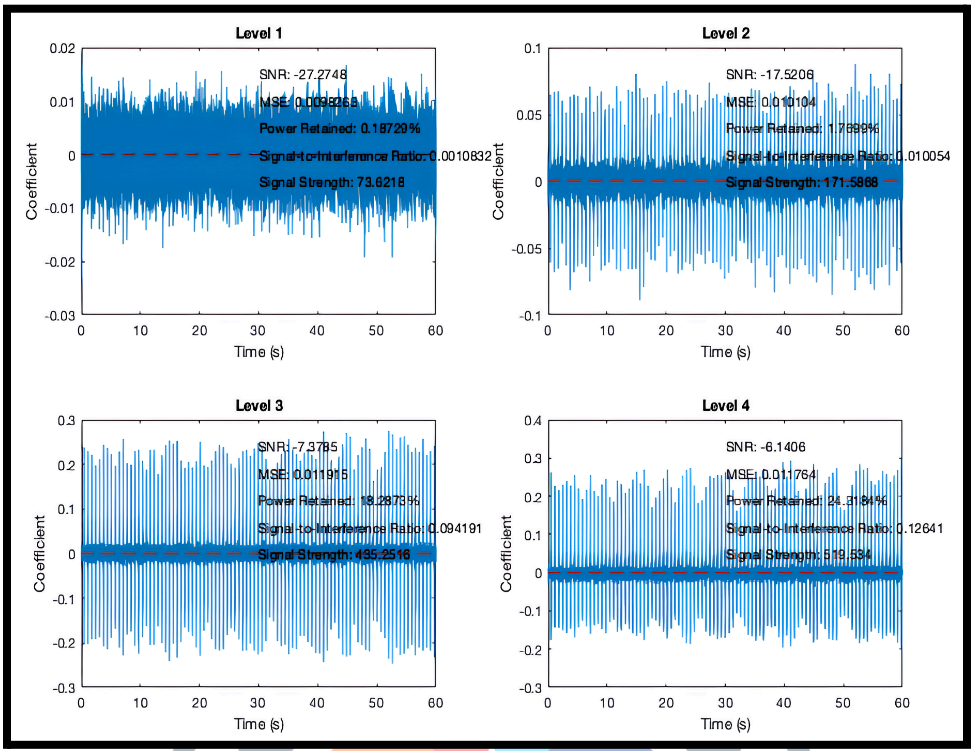

figure 6. IIR butterworth filter

IV. COMPARATIVE ANALYSIS

To measure the denoising performance of FIR kaiser window-based method and IIR butterworth filter, a comparison is performed between these two techniques. Both of these filtering technique are used in various ECG records, which are tabulated in **Table 1**:

Table 1: Comparison of FIR kaiser window and IIR butterworth filters using statistical parameters at each level of DWT

It is concluded from **Table 1** that the filters offer distinct merits: FIR Kaiser Window filters provide excellent frequency response control and linear phase characteristics, while IIR Butterworth filters offer efficient computational performance due to their recursive nature. By evaluating the performance of these filters in terms of noise reduction and signal preservation, this study helps in making decisions about which filter design best aligns with their specific application requirements [12,13].

Statistical Parameters							
Arrhythmia Signals	**DWT**	**FIR Kaiser Window**			**IIR Butterworth Filter**		
Records	**Levels**	**SNR**	**Signal Strength**	**Power Retained (%)**	**SNR**	**Signal Strength**	**Power Retained (%)**
100m.mat	**1**	**-24.001**	**87.461**	**0.428**	**-26.962**	**81.169**	**0.201**
	4	**-2.242**	**573.588**	**54.778**	**-5.171**	**572.371**	**30.401**
118m.mat	**1**	**-32.519**	**102.311**	**0.056**	**-36.709**	**101.494**	**0.021**
	4	**-4.458**	**1468.688**	**35.823**	**-8.509**	**1468.342**	**14.093**
124m.mat	**1**	**-28.795**	**70.596**	**0.131**	**-37.115**	**70.522**	**0.019**
	4	**-5.355**	**524.465**	**29.137**	**-13.43**	**523.724**	**4.539**
136m.mat	**1**	**-21.748**	**105.611**	**0.668**	**-31.074**	**89.445**	**0.078**
	4	**-0.943**	**953.393**	**80.468**	**-8.925**	**952.829**	**12.806**
148m.mat	**1**	**-15.732**	**108.529**	**2.671**	**-33.467**	**75.695**	**0.549**
	4	**-0.529**	**673.318**	**88.526**	**-7.241**	**500.347**	**20.385**
156m.mat	**1**	**-20.967**	**93.793**	**0.325**	**-32.907**	**73.621**	**0.805**
	4	**-1.879**	**544.882**	**79.481**	**-5.905**	**519.534**	**18.739**
164m.mat	**1**	**-23.758**	**89.215**	**2.935**	**-30.047**	**79.941**	**0.115**
	4	**-2.336**	**531.801**	**64.529**	**-6.529**	**538.834**	**21.562**
178m.mat	**1**	**-26.923**	**74.615**	**0.827**	**-28.269**	**65.967**	**0.138**
	4	**-4.595**	**529.483**	**61.948**	**-8.191**	**607.582**	**23.813**
234m.mat	**1**	**-22.812**	**84.307**	**0.523**	**-27.274**	**73.621**	**0.187**
	4	**-2.779**	**520.605**	**52.728**	**-6.141**	**519.534**	**24.318**

V. CONCLUSION

In conclusion, the integration of a 4-level Discrete Wavelet Transform in ECG signal processing facilitates intricate multi-resolution analysis, essential for distinguishing high- and low-frequency components. The comparative analysis highlights the superiority of the FIR Kaiser Window filter over the IIR Butterworth filter in ECG signal processing. The FIR Kaiser Window filter ensures better preservation of essential signal components, superior fidelity in signal reconstruction, and better noise reduction capabilities compared to the IIR Butterworth filter. These findings emphasize the potential of FIR Kaiser window filters to enhance the accuracy and reliability of ECG signal analysis, aiding in the detection of subtle cardiac abnormalities in clinical research contexts.

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