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Noise Suppression of ECG Signal Using Optimized Digital Butterworth Bandpass Filter

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Abstract

ECG devices have been widely utilized by medical experts for cardiac health detection. It generates an analog signal that has intrinsic characteristics represented by PQRST waves. Each wave is useful for diagnostic purposes. However, ECG signal is prone to noise, p articularly EMG noise. This noise occurs as a result of muscle contraction or sudden body movement of a subject. Several studies have been proposed to suppress the EMG noise on ECG. However, the complexity of an algorithm is a challenging task to be solved. Considering this problem, this research aims to suppress EMG noise using a low-complexity algorithm. To achieve this objective, a method of Butterworth bandpass filter DF-II has been proposed. The findings demonstrate that the proposed method improves SNR and signal power by 0.498dB and 0.006dBm/Hz respectively. It also demonstrates the capability to perform efficiently on a microcontroller unit.

A. Introduction

In the medical field, Electrocardiogram (ECG) is an essential device used to diagnose the cardiac health of a subject. It generates an analog signal, which is called an ECG signal. Medical experts utilize this signal for various purposes such as heartbeat analysis, biometric analysis, and emotion recognition [1].

ECG signal is prone to noise. There have been 3 types of noise including, Baseline Wander (BW), Power-Line Interference (PLI), and Electromyography (EMG) [2]. The electrode, capacitive-inductive actions, and muscle movement are possible sources of these noises. The aforementioned noises lie between frequencies of 0.01-100 Hz.

BW and PLI noises have narrow bandwidth. Both can be mitigated using a simple Low Pass Filter (LPF). Conversely, EMG noise has a larger bandwidth thus, making it more difficult to preprocess the signal [3]. An ECG signal contaminated with noise may result in a failure diagnosis of arrhythmia disease.

As mentioned previously, BW noise lies in the lower frequency. A study on BW suppression was proposed using Hilbert vibration decomposition method [4]. It performs better than empirical mode decomposition, however, the complexity is an issue to be addressed. BW could also be suppressed by improving electrode quality as proposed by [5]. The latest study on BW suppression method was done by [6], using a decomposition technique based on Sparrow Search Algorithm (SSA). Electromagnetic waves and PLI can also produce lower-frequency noise. To reduce the noise, an adaptive moving average technique was proposed [7]. It generates an ECG signal with the Signal-to-Noise Ratio (SNR) and frequency of 44 dB and 10 Hz respectively.

Multiple noises may occur simultaneously on the ECG signal. Thus, there have been studies to mitigate this issue. The experiment was done by incorporating artificial noise into the raw ECG signal. BW and PLI occur simultaneously was minimized using Eigen and Fourier decomposition [8], [9]. The combination of Gaussian, PLI, EMG, and BW noises was mitigated using the Wiener filter and Kalman filter [10].

However, suppressing multiple noises is an arduous task, it also takes tremendous resources out of the processing unit. Hence, this research centers only on EMG noise. EMG is selected due to the inherent characteristic of this noise, that is, taking place at the same frequency as that of ECG. [11] proposed a method to minimize EMG noise using Finite Impulse Response (FIR) LPF digital. However, a complex Field Programmable Gate Array (FPGA) is required for computation. Further study on EMG noise suppression was carried out with the assistance of SSA method [3]. It executes the task successfully, but computational cost is not considered.

To address the computational cost issue, [12] proposed a noise removal method using Butterworth LPF. However, the performance is not up to the mark as the original signal is filtered as well. Considering the disadvantages of previous method, this study aims to suppress EMG noise on ECG signal by taking filter accuracy and computational cost into account. The Butterworth Band Pass Filter (BPF) algorithm proposed by [13] is optimized into Direct Form-II (DF-II). This is carried out to filter the signal in specific frequencies while at the same time reducing the complexity of algorithm.

B. Research Method

This section outlines the methodology employed in this research including, mathematical modeling, system architecture, and research method.

Mathematical Modeling

According to [14], a Nth-order transfer function of Butterworth LPF is represented in equation 1. Where $B_n(s)$ is Nth-order Butterworth polynomials. Assume that a_n is a filter coefficient of n, it results in equation 2. Subsequently, it is transformed to analog BPF using equation 3.

$$H(s) = \frac{1}{B_n(s)} \tag{1}$$

$$H(s) = \frac{1}{\sum_{n=0}^{N} a_n s^n} \tag{2}$$

$$H_p(s)|_{\frac{s^2+\omega_0^2}{Ws}} = \frac{1}{\sum_{n=0}^{N} a_n \left(\frac{s^2+\omega_0^2}{Ws}\right)^n} \tag{3}$$

Where ω_0 is a frequency warping of BPF. Bandwidth of BPF denoted by W, is a difference between High Pass Filter (HPF) and LPF frequency warping. The final solution is then transformed to general Linear Time-Invariant (LTI) system through equation 4. It consists of numerator and denominator that will be used as the filter coefficients.

$$H(z) = \frac{b_0 + b_1 z^{-1} + \cdots + bNz^{-N}}{a_0 + a_1 z^{-1} + \cdots + aNz^{-N}} \tag{4}$$

Numerator and denominator denoted by b and a respectively. These are filter coefficients of Nth-order Butterworth BPF. Number of coefficients is directly proportional to filter order. In order to use these coefficients in other processing unit, inverse z-transform is performed resulting in equation 5. The final solution is shown in equation 8, that is a difference equation of Nth-order BPF.

$$\frac{Y(z)}{X(z)} = \frac{b_0 + b_1 z^{-1} + \cdots + b_N z^{-N}}{1 + a_1 z^{-1} + \cdots + a_N z^{-N}} \tag{5}$$

$$B[n] = b_0 x[n] + b_1 x[n-1] + \cdots + b_N x[n-N] \tag{6}$$

$$A[n] = a_1 y[n-1] + \cdots + a_N y[n-N] \tag{7}$$

$$y[n] = B[n] - A[n] \tag{8}$$

System Architecture

In order to validate the performance of proposed filter method, a hardware verification is performed by means of a microcontroller. The system architecture is divided into 2 main blocks such as the AD8232 ECG sensor and ESP32 microcontroller unit as illustrated in figure 1. AD8232 acts as instrumentation amplifier to preprocess an input signal collected from a healthy adult volunteer [15].

Subsequently, amplified analog input signal is transformed to digital signal via ADS1115. ADS1115 is an integrated circuit whose purpose is to sample analog signals with the resolution of 16-bit. Then, this digital signal will be filtered using 32-bit microcontroller unit.

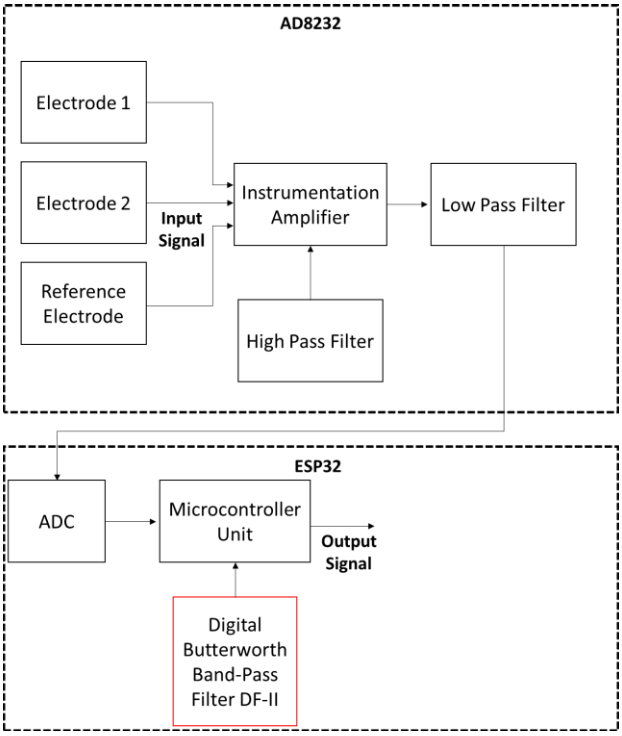

Figure 1. System Architecture of ECG device

Figure 1 shows that the proposed method takes place in ESP32 block as highlighted in red. This process is carried out by using filter coefficients derived from equation 8. Further explanation of this method is described in the following section.

Digital Butterworth Bandpass Filter DF-II

Equation 8 represents a difference equation in the form of Direct Form-I (DF-I). In general, there is no significant difference between DF-I and DF-II. However, the delay unit denoted by z^{-1} decreases as shown in figure 2. Consequently, it results in better computational time compared to that of DF-I.

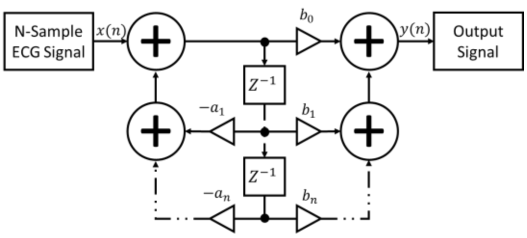

Figure 2. Block Diagram of Proposed Butterworth BPF DF-II

$$w[n] = x[n] - a_1 w[n-1] - \cdots - a_N w[n-N] \tag{9}$$

$$y[n] = b_0 w[n] + b_1 w[n-1] + \cdots + b_N x[n-N] \quad (10)$$

Initially, DF-II implements a similar normalized transfer function as that of DF-I. However, it is divided into 2 parts represented by $w[n]$ and $y[n]$. Coefficients of the denominator constitute $w[n]$ as shown in equation 9. Then it is substituted into $y[n]$, resulting in the final solution shown in equation 10.

C. Result and Discussion

This section examines the simulation results of proposed BPF method. The findings are presented to assess filter performance in reducing the noise, followed by a comparison with previous study [12], [13]. In addition, hardware implementation is carried out to verify the efficiency of algorithm.

Simulation Results

The simulation is performed using Matlab software with the samples taken from a healthy adult volunteer through a 3-electrode ECG device. Initially, the signal spectrum is calculated to determine the frequency at which the noise is present. Therefore, the signal should be transformed into a frequency domain using Fourier transform as shown in figure 3.

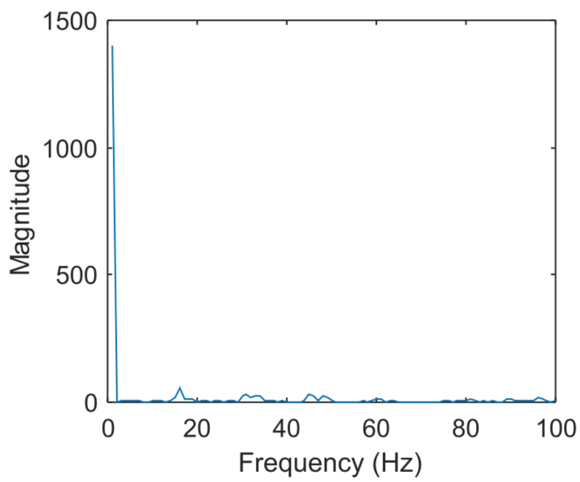

Figure 3. ECG input signal in frequency domain

It shows that the noise spectrum is exceptionally high at the frequencies of 0-50Hz. Taking this into account, a bandpass filter should be designed between these frequencies. Filter order is determined by considering the magnitude response as shown in figure 4. It can be seen that the response gets better as the order increases. In the Butterworth BPF, a number of polynomials is equal to $Nx2$. Therefore, the filter is limited to 4[th] order to prevent memory overflow during hardware verification.

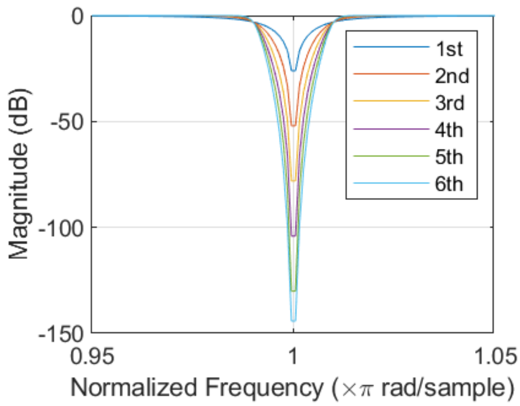

Figure 4. Frequency response of Butterworth BPF DF-II

Figure 5(a) shows an Nth sample ECG input signal collected from a volunteer. The intrinsic properties of this signal are displayed in table 1. Assuming that the signal is ideal, a random EMG noise with an amplitude of 0.1V is applied as shown in figure 5(b). It ranges in the frequencies of 30-45Hz.

Table 1. Characteristics of ECG input signal

Parameter	Value
Sampling frequency: f_s/HZ	860
Signal frequencies: f/Hz	0-50
Bandwidth: W/Hz	50

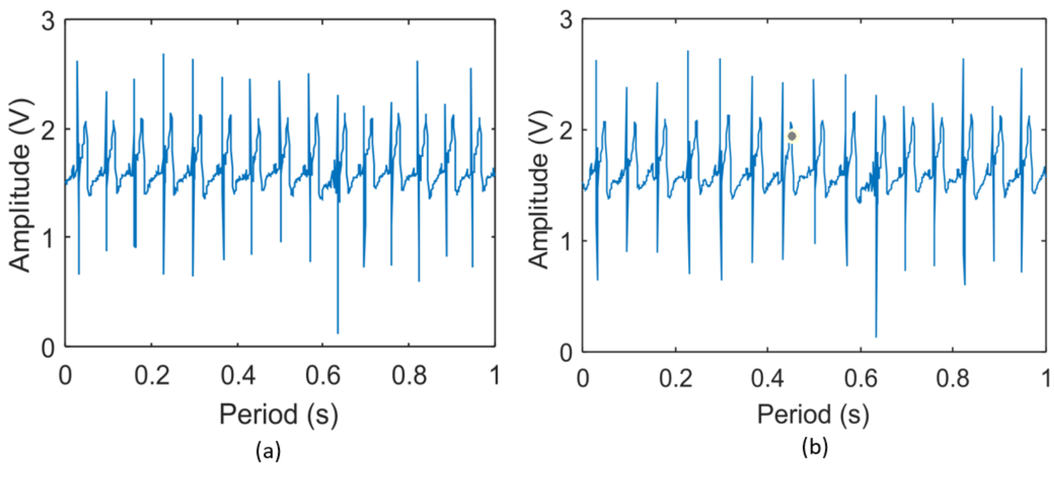

Figure 5. ECG signal sampled with frequency of 860 Hz (a), ECG signal + artificial EMG noise (b)

Table 2. Simulation parameters

Parameter	Value
Low cutoff frequency: f_{cl}/Hz	0.001
High cutoff frequency: f_{ch}/Hz	49.5
Filter order: N	4

ECG signal is sampled with a span of 1s. A full-cycle of the signal denoted by PQRST is completed with a period of 0.07s. Thus, there is a total of about 15 signals being plotted. Table 2 shows the simulation parameters of proposed model. As mentioned previously, the noise spectrum lies between 30 and 45Hz frequencies. Considering the aforementioned, cutoff frequencies are determined accordingly. After a thorough experiment, it is found that the optimum cutoff frequencies lie between 0.001 and 49.5Hz which represent low and high cutoff frequencies respectively.

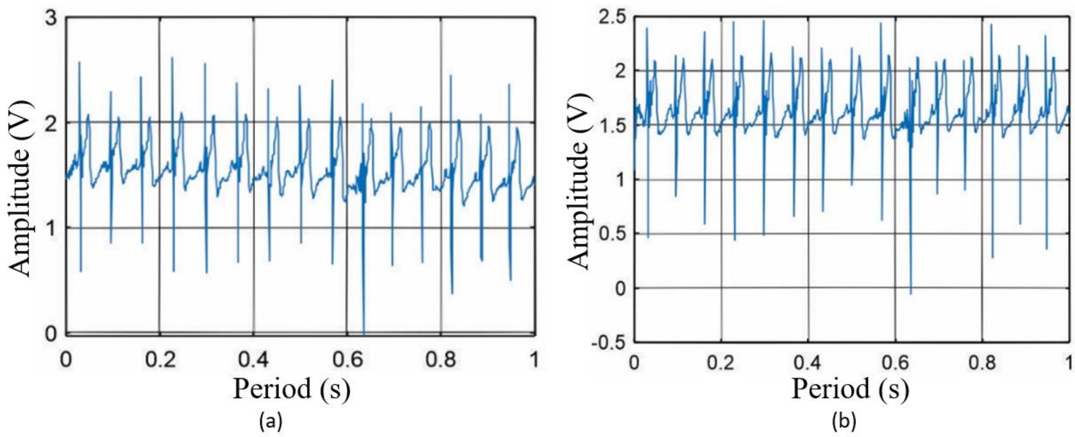

Figure 6. Filtered ECG signal using Butterworth LPF (a), filtered ECG signal using Butterworth BPF DF-II (b)

Hardware Verification

The hardware implementation circuit is associated with the proposed architecture depicted in figure 1. Testing hardware is shown in figure 7. It is employed to verify how well the proposed method works on a low-cost microcontroller.

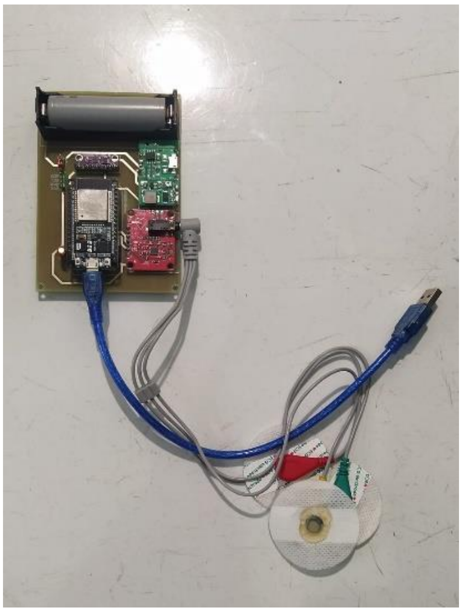

Figure 7. Testing Hardware

The raw ECG signal recorded using testing hardware is represented in figure 8. A full-cycle PQRST signal is sampled with a period of 1s. Even though BW noise persists on the signal, this study focuses solely on EMG noise. Then, artificial EMG noise is applied as shown in figure 9(a).

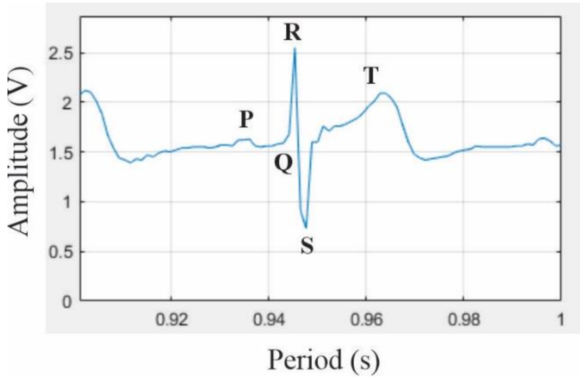

Figure 8. ECG input signal recorded by testing hardware

As a result of random EMG noise, the signal amplitude around the P region increases by 0.1V. Consequently, multiple P waves occur, which alter the inherent characteristics of the ECG signal. To suppress this noise, BPF DF-II is applied. Figure 9(b) highlights that noise amplitude is noticeably suppressed. However, it removes wave features, particularly around the P region. This situation arises as a result of the filter removing the signal at frequency overlap.

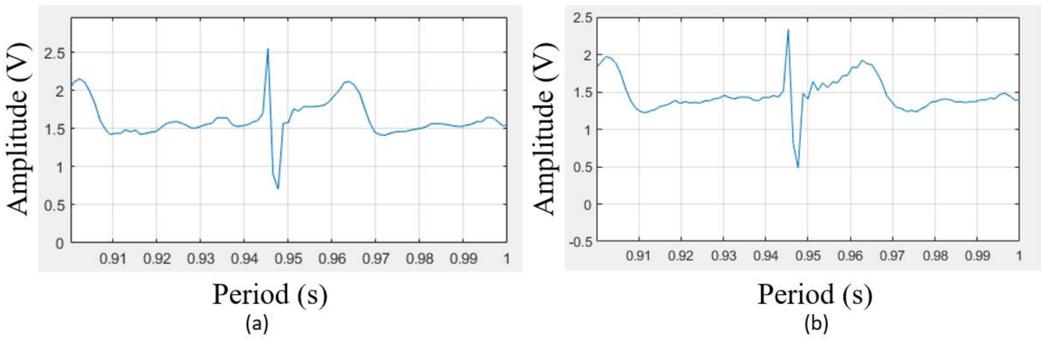

Figure 9. ECG signal + artificial EMG noise (a), ECG signal filtered using Butterworth BPF DF-II (b)

Table 3. Performance comparison between proposed method and Butterworth BPF DF-I

	Butterworth BPF DF-I [13]	**Proposed Method**
Processing Time (s)	5.960	5.930
Memory Usage (KB)	101.560	101.536

To assess the performance of proposed method on processing unit, it is then compared with the DF-I algorithm. Initially, Butterworth DF-II generates the same wave output as that of DF-I. However, DF-II is employed due to its capability in reducing the global variables. Table 3 illustrates that the processing time reduces in proportion to the decrease in global variables. The findings demonstrate that proposed BPF method is proven to be more efficient in terms of processing time and memory usage, with the values of 0.03s and 0.024KB respectively.

Table 4. Performance comparison between proposed method and Butterworth LPF

	Butterworth LPF [12]	**Proposed Method**
SNR (dB)	0.016	0.614
Signal Power (dBm/Hz)	0.0792	0.0850

The performance of proposed BPF method has been proved through in-depth experiments. The findings highlight superior performance of proposed BPF filter as opposed to LPF. To sum everything up, the comparison between LPF and the proposed BPF is presented in table 4. The SNR represents the ratio of signal power to noise power. This parameter is obtained by transforming output signal to frequency domain followed by power spectrum calculation. According to the findings, proposed BPF outperforms LPF algorithm in terms of SNR and signal power by 0.498dB and 0.006dBm/Hz respectively.

D. Conclusion

In this research a method of Butterworth BPF DF-II has been proposed. This research aims to suppress noise with the aid of a low-complexity algorithm. The findings highlight the significance of proposed method in suppressing noise, while at the same time reducing the complexity of algorithm. The results show that processing time and memory usage have been reduced by 0.03s and 0.024KB respectively. Moreover, the proposed method improves SNR and signal power with respect to LPF method by 0.498dB and 0.006dBm/Hz respectively. Improving SNR means that the noise is suppressed further with respect to original signal. Nevertheless, there have been altered wave features, particularly around P region. Taking this issue into account, future research on EMG noise suppression can be carried out without altering inherent characteristics of ECG signal.

E. Acknowledgment

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