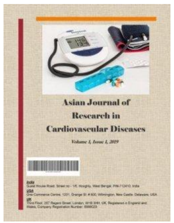

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Comparative Analysis of Savitzky-Golay and Butterworth Filters for Electrocardiogram De-Noising Using Daubechies Wavelets

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Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by authors SSD, FCM, IU, AZL and LWL. The first draft of the manuscript was written by author FCM reviewed and re-drafted by author SDY and then all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Introduction: Electrocardiogram (ECG) provides a wealth of information and remains an essential part of the assessment of cardiac patients. However, noise distortions associated with the signal could lead to wrong interpretation and diagnosis.
Aim: To carry out an extensive comparative analysis of Savitzky-Golay (S-G) and Butterworth filters for ECG de-noising using Daubechies wavelets in a MATLAB version 2015a.
Methodology: Noisy ECG signals downloaded from physionet.org under MIT-BIH arrhythmia database were de-noised using S-G and Butterworth filters displayed in both time and frequency domains. A quantitative evaluation was done to assess the performance of the filters for Signal to Noise Ratio (SNR), Mean Square Error (MSE) and Signal to Interference Ratio (SIR). The results of SNR for this work are compared with the results of other researches with other methods.
Results: Experimental result for de-noising with Butterworth filter shows abnormal spiky waves in time domain quite unusual in morphology of the original waves and in the frequency domain creates

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image signals which are indications of noise and baseline drift. While S-G filter maintains the signal power constant and only tries to decrease the noise power with peak preservation. Performance analysis for SNR, MSE and SIR using Butterworth filter gives mean values of 1.63 dB, 0.2036 and 0.259 dB, while that of S-G filter gives 32.78 dB, 0.0001 and 1852.358 dB respectively.

Discussion: Significant reduction of noise by S-G filter and retaining the ECG signal morphology effectively as compared to Butterworth filter is an evident that S-G filter delivers better performance results as compared to Butterworth filter in terms of noise separation, artifacts and baseline drifts.

Conclusion: The importance of ECG de-noising filters and the criteria for their selection must be clearly understood by hospital managements and cardiac health centers for good quality ECG in diagnosis and therapy for cardiac diseases.

Keywords: Electrocardiogram (ECG); Savitzky-Golay filter; Daubechies wavelets; butterworth filter; de-noising technique; signals.

1. INTRODUCTION

Electrocardiogram is the electrical activity of the heart which is a graphical demonstration of the variation of bio potential versus time [1]. It can also be defined as a bio electric signal which is used to take into account the electrical activities of the heart [2]. It is a non-invasive test used in determining the regular rhythmic activities of the heart condition [3,4,5]. According to Ravandale and Jain [4], and American Heart Association [6] this test is done over time to help in the study and understanding of cardiac disease. As such doctors and patients can effectively and continuously monitor the patient's heart activities [7]. Shanmugasundaram et al. [8] and Walraven [9] had pointed out that ECG signal carries information about the structure and function of the heart which normally has a dynamic range of 0.05–100 Hz and 1–10 mV. According to Harjeet and Rajini [10] and Libby et al. [11] some of the information includes heartbeats rhythm, heart position and conduction disturbances, diagnose damages done to the muscle cells (of the heart), Relative chamber size, effects of drugs on heart condition, change in electrolyte concentration etc.

ECG signals can easily be recorded using non-invasive electrodes on the limbs or chest or on a patient's torso [7,12,10,13]. These electrodes are biological transducers consisting of metals and salts [14]. A good quality ECG is used by clinicians to enable them interpret and identify pathological and physiological phenomena which is commonly used to checkmate causes of chest pain and abnormal heart rhythm. Little electrical transforms on the skin that arises because of those heart muscle movements is being detected by electrodes then displayed on the screen as a 1D biological signal. Fisch [15] had argued that ECG can be the first or only indication of a possible cardiac disease. However, in recording of ECG signals, noise interference also known as artifacts always accompanies the signal and can only be minimized to a barest and interpretable minimum [8]. This noise comes in low frequency, high frequency or physiological interferences due to different factors including Baseline Wandering, Power Line Interference (PLI), Motion Artifact, Electrode Contact Noise or Muscle Contraction [16].

Baseline wander noise (drift) is caused by respiration, patient movement, dirty lead wires or electrodes, loose electrodes etc. [7,17]. It is usually within the range of 0.15 Hz – 0.3 Hz [4]. According to Kasar and Josh [18], because of the baseline wander, peak-T is higher than peak-R and in most times mistaken for peak-R and has a 15% amplitude variation of peak-to-peak. Power Line Interference is majorly caused by poor grounding of the ECG machine, which can create difficulty in reading and interpreting waveforms of low amplitude. According to Garg et al. [19] PLI constitute most part of the distortion at 50-60Hz, and its amplitude is 50% of peak-to-peak ECG amplitude. Motion Artifacts are transient baseline changes usually caused by impedance mismatch between electrode and the skin due to patient movement while ECG is being recorded [20,21]. Electrode Contact Noise occurs due to improper contact between the electrode and skin of the patient. It has a short duration of 1 sec. [18]. Muscle Contraction or Electromyography (EMG) noise is caused by the movement of the patient and is responsible for the generated potentials (in milli-volt level) [20].

To avoid misinformation about the disease, the removal of artifacts/Noise in ECG signal is an important pre-processing action to abnormality detection from the waveforms. El-Dahshan [22] proposed an effective hybrid scheme for the denoising of ECG signals corrupted by nonstationary noises using the GA and DWT. Rastogi and Mehra [16] proposed the analysis Butterworth and Chebyshev filters for ECG de-noising utilizing wavelets. Joshi et al. [21] proposed the ECG signal de-noising techniques using various approach based on wavelet transformation, fuzzy logic, FIR filtering, and empirical mode decomposition (EMD). Rastogi and Mehra [23] analyze the Savitzky-Golay filter for baseline Wander suppression in ECG using wavelets. Sadhukhan and Mitra [24] proposed an ECG noise reduction technique by suppressing the Fourier coefficient corresponding to the noise band. Hitrangi Sawant and Harishchandra [25] proposed the ECG signal denoising using discrete wavelet transform. Balan *et al.* [26] proposed the underwater noise reduction method using wavelet and Savitzky-Golay. Sharma and Narwaria [27] proposed the window based FIR filter to assess the effectiveness of various window techniques for noise suppression in ECG signal. Xin et al. [17] proposed the ECG baseline wander removal based on mean-median filter and empirical mode decomposition. Krishnamurthy et al. [28] compared various filtering techniques (digital filters) for removing high frequency noise in ECG signal. Sharma and Suji [13] analyzed various window techniques for de-noising each ECG signal based on FIR filters. Harjeet and Rajini [10] performed ECG signal de-noising using Savitzky-Golay filter and Discrete Wavelet Transform (DWT). Alyasseri et al. [29] performed denoising by using β-hill climbing algorithm with wavelet transform. Md Yusof and Ariffin [30] proposed the Steins Unbiased Risk Estimate (SURE) method to optimize the level of decomposition in stationary wavelet transform de-noising. Ahmad et al. [31] proposed the Genetic Algorithm (GA) with wavelet transform (WT) for de-noising of arrhythmia ECG signals. Wedeld [32] proposed the normalized least mean square filter to carry out preliminary processing of ECG signals for use in multivariate analysis. Wedeld estimated and extracted the baseline wandering and shift from the signal by using Savitzky-Golay filter, discrete wavelet transforms and an empirical mode decomposition and also implemented algorithm for detecting QRS complexes and estimating heart rate.

The use of filters in ECG de-noising has proven to be one of the most effective ways to obtain a good and quality signal. In this study a comparative analysis of Butterworth and Savitzky-Golay (S-G) filters for ECG signal de-noising using Daubechies wavelets was carried out with the help of MATLAB version 2015a. The research is timely in this period of COVID-19 Pandemic as it will serve as a guide for hospital managements and cardiac health centers in understanding the parameters for the selection of appropriate de-noising filters for an improve and effective ECG signal for medical diagnosis and treatment of cardiac related diseases.

2. LITERATURE REVIEW

2.1 Savitzky-Golay (S-G) Filters

In 1964, Savitzky and Golay proposed a way of retaining the original signal shape, and thus, its information while still using the principles of moving average filters [33]. Moving average filter is one of the simplest and most straightforward ways of filtering a noisy signal [32]. The generalized formulae of the repeated process of averaging in order to filter this signals is as shown in Eqn. 1.

$$g_k = \sum_{i=k-m}^{k+m} C_i X_k \tag{1}$$

where;

- C_i =Filters coefficient with constant value $\frac{1}{n}$
- X_k =A random point of a discrete data set
- m =Static number

In order to do so, they sought to replace C_i in Eqn. 1 with polynomials of higher order. To do this, they proposed an approximation of local least-square polynomial [34] fitting the polynomial line to the $'n'$ points within the window. The criteria used in choosing the filtered value $g_k$is by considering the value which best retain the fundamental shape of the data; the coefficient of each polynomial must be determined so that the equivalent polynomial curve best matches the data provided [35].

Mathematically, the idea is to find the best mean-square fit of a polynomial of say, degree p via a set of $2m+1$ consecutive values, where $p < 2m+1$. This according to [32] is of the form:

$$g_k = \sum_{i=0}^{i=p} b_{pi} k^i = b_{p0} + b_{p1}k + b_{p2}k^2 + \cdots + b_{pi}k^p \tag{2}$$

Taking the first and second order derivatives of Eqn. 2 we have:

$$\frac{d_g k}{dk} = b_{p1} + 2b_{p2}k + 3b_{p3}k^2 + \cdots + pb_{pp}k^{p-1} \tag{3}$$

$$\frac{d_gK}{dk^2} = 2b_{p2} + 6b_{p3}k + \cdots + (p-1)pb_{pp}k^{p-2} \quad (4)$$

Generally written;

$$\frac{d_g^pK}{dk^p} = p^b{}_{pp} \quad (5)$$

By the least squares criteria, it is required to minimize the sum of the squares of the difference the observed values y_k and estimate values inside the window, thus;

$$\frac{\partial}{\partial b_{pi}}\left[\sum_{k=-m}^{k=m}(g_k - y_k)^2\right] = 0 \quad (6)$$

Expressing Eqn. 6 with respect to b_{pk} gives:

$$\frac{\partial}{\partial b_{pk}}\left[\sum_{k=-m}^{k=m}\left(b_{p0} + b_{p1}k + \cdots + b_{pp}k^p - y_k\right)^2\right]$$

$$=2\sum_{k=-m}^{k=m}\left(b_{p0} + b_{p1}k + \cdots + b_{pp}k^p - y_k\right)k = 0 \quad (7)$$

Conclusively, S-G filter has an important peak preserving property which is very useful in ECG signal analysis [36].

2.2 Butterworth Filter

Butterworth filter is a form of high order filter, designed to have a very flat response (i.e. no ripples) in the pass band [37,16] and steep slope immediately after cut-off. In order to achieve this, Butterworth [38] proposed a filter design with a possible gain or frequency response which is defined as follows:

$$G(\omega) = \frac{1}{\sqrt{1+\varepsilon^2(\frac{w}{w_c})^{2n}}} \quad (8)$$

Where;

ω = Angular frequency (rad^{-s})
n = Number of poles in the filter, which is same as the amount of reactive elements of a passive filter.
ε =Maximumpass band gain
ω_c = Cut-off frequency
G = Transfer function
With, $\varepsilon = 1$ and in a more linear form, Eqn.1 can be re-written as;

$$\frac{V_{out}}{V_{in}} = \frac{1}{\sqrt{1+(\frac{f}{f_c})^{2n}}} \quad (9)$$

Where;

f = Frequency at which calculation is made
f_c = The cut-off frequency usually half power or -3dB

Butterworth [38] created a higher order filters from a bipolar filters which are kept separate from each other by a vacuum tube amplifier.

2.3 Methods of ECG Analysis

Various methods have been developed for ECG analysis including Fast Fourier transform, Short time Fourier transform, and wavelet transform.

2.3.1 Fast Fourier Transform (FFT)

According to Rawal et al. [39] and Karpagachelvi et al. [40] the time domain method has been used in early times for ECG signal analysis, but it was not sufficient to study all characteristics of ECG signal. Fast Fourier Transform (FFT) method transforms time domain signal to frequency domain to obtain the frequency coefficients [41]. According to Singh et al. [42], it is an elementary transform in digital signal processing with various applications in frequency analysis, signal processing etc. The FFT can be defined as follows:

$$XK = \sum_{n=0}^{N-1} xe^{-\frac{nk2\pi i}{n}} \quad (10)$$

Where k is an integer ranging from 0 to N-1

According to Tasa et al. [43] FFT is one of the varieties of techniques used to compress ECG signals using the following steps:

- Obtaining an ECG sample or input signal.
- Compressing the input signal by removing the low frequency components.
- Recovery of the original signal by using inverse FFT.

However, according to Gautam and Kaur [1] FFT has a disadvantage that it failed to provide the information regarding the accurate location of frequency components in time.

2.3.2 Short Time Fourier Transform (STFT)

Short-Time Fourier Transform (STFT) also called Gabor transform is an attempt to overcome the shortcoming of FFT since it has both time and frequency information [41,44]. The STFT determines the sinusoidal frequency and phase content of the signal as it varies with time using a simple and fast technique called spectrogram, i.e. by slicing the waveform of interest into a number of short data segments using a window function, then analyzes each segment using standard Fourier transform [45]. For a signal x (t), the STFT can be defined as follows:

$$X(\tau, f) = \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t) w\left(t - \tau e^{-i2\pi ft}\right) dt \qquad (11)$$

Where w (t) is a window, having duration T, centered at time location t, then the Fourier transform of the windowed signal x (t) w (t - τ) is the STFT.

According to Rajini and Kaur [45] STFT has a limitation in that its time frequency precision is not optimal as window should always have a fixed size and thus it does not give multi resolution information of the signal.

2.3.3 Wavelet transform

A Wavelet as defined by Alfouri and Daqrouq [46] is a small wave which has energy concentrated in time and provides a tool for the analysis of transient, non-stationary or time-varying signals. According to Karthikeyan et al. [47] the Wavelet Transform has the multi resolution property which gives both time and frequency information through variable window size. Rajini and Kaur [45] added that it is used in signal compression as well as a new tool for seismic signal analysis. Various Wavelets are available for large variety of applications including Biorthogonal, Haar, Coiflet, Symlet, Daubechies Wavelets, etc. However, in this study, the Daubechies Wavelets was chosen specifically the db4 because of its close similarity to ECG in terms of tracings and its property of maximum number of vanishing moments [23]. Some features which make the Wavelets useful have been itemized by Nagendra et al. [48] as follows:

- Wavelets are localized in both time and frequency.
- For analyzing non-stationary signals such as ECG which have frequent level variations and uneven features.
- Wavelet separates a signal into multi-resolution components.

The Wavelet Transform is a linear process that decomposes the signal into a number of scales associated with frequency components and analyzes each scale with a certain resolution [49]. Unlike the Fourier analysis which is restricted to one feature morphology (i.e. sinusoid), Addison [50] argued that in the Wavelet technique various Wavelet functions are available, that allows selecting the best function for analyzing the signal. The Wavelet transforms can be classified into two categories: Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transforms (DWT).

Continuous Wavelet Transform: The Continuous Wavelet Transform (CWT) is a time–frequency analysis method which differs from the traditional STFT. It is a technique that allows high localization in time of high frequency signal features by having a variable window width, which is associated to the scale of observation for the isolation of the high frequency features [45]. It differs from the STFT in that it is not restricted to use of sinusoidal analyzing functions, rather, localized waveforms can be selected as long as they satisfy the predefined mathematical criteria [50]. The CWT of a signal x (t) is defined by Nagendra et al. [48] can be given as:

$$w(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) h * \left(\frac{(t-b)}{a}\right) dt \qquad (12)$$

Where, h (t) is called mother wavelet, and is the scaling parameter in y-axis and b is the shift parameter in x-axis.

Discrete Wavelet Transform: The Discrete Wavelet Transform (DWT) as defined by Gautam and Kaur [1] can be given as:

$$w(j, k) = \sum_j \sum_k x(k) e^{-\frac{j}{2}} \varphi(2^{-j} n - k) \qquad (13)$$

where Ψ (t) is a time function with finite energy and fast decay called the mother wavelet.

3. MATERIALS AND METHODS

3.1 Materials

The materials and their specifications used for the purpose of this research includes windows 10 laptop with 1.6Hz processor, 3.85 usable Ram, and 64-bit operating system, MATLAB version 2015a, and noisy ECG signal obtained from physionet.org under MIT-BIH arrhythmia database.

3.2 Methods

3.2.1 Signal de-noising method

The method involved in this research was carried out according to the following steps:

i. Download the noisy signal from physionet.org which is in time domain.
ii. Convert to wavelet (Frequency) domain using MATLAB soft-ware.
iii. De-noise the signal with the Butterworth filter using Daubechies wavelets.
iv. De-noise the signal with the Savitzky-Golay filter using Daubechies wavelets.
v. Convert the de-noised signals back to time domain

3.2.2 Performance analysis method

To check the performance of the filter various analysis were carried out which includes the calculation of Signal to Noise Ratio (SNR), Mean Square Error (MSE) and Signal to Interference Ratio (SIR).

3.2.2.1 Signal to noise ratio (SNR)

The signal to noise ratio (SNR) compares the level of desired signal to the level of background noise. Sources of noise can include microwave ovens, cordless phone, Bluetooth devices, wireless video cameras, wireless game controller, fluorescent lights, and more [51]. The noise does not include co-channel interference from other radio transmitters. According to Net Spot [51], a ratio of 10-15dB is the accepted minimum to establish an unreliable connection, 16-24dB is usually considered poor; 25-40dB is good and a ratio of 41dB or higher is considered excellent. The SNR value can be calculated using the following equations:

$$\mathrm{SNR_{dB}} = 10(\frac{\mathrm{S}}{\mathrm{N}})_\mathrm{P} \tag{14}$$

Or,

$$\mathrm{SNR_{dB}} = 20(\frac{\mathrm{S}}{\mathrm{N}})_\mathrm{v} \tag{15}$$

Where;

S = RMS power of ECG signal
N = RMS power of the de-noised ECG signal

3.2.2.2 Mean square error (MSE)

The mean square error (MSE) measures the average of the squares of the errors, that is, the average square difference between the estimated value and the actual value. It measures how close fitted line is to data point and provides us with confidence that our assumptions about trends in the data are correct. The smaller the MSE value the better the fit, as smaller values imply smaller magnitudes of error [52]. The MSE value was calculated using the following equation:

$$\mathrm{MSE} = \frac{\sum(\mathrm{s}-\hat{\mathrm{s}})^2}{\mathrm{N}} \tag{16}$$

Where;

s = Noisy signal
$\hat{\mathrm{s}}$ = De-noised signal
N = Number of samples

3.2.2.3 Signal to interference ratio (SIR)

The signal to interference ratio (SIR) is similar to SNR but here the interference is specific to co-channel interference from other radio transmitters. According to Nnebe et al. [53] the higher the SIR the minimal the interference and the SIR must reach a minimum threshold for the signals to be detected. Suksompong [54] explained that SIR should be greater than a specified threshold for proper signal operation. In the 1G AMPS system, designed for voice calls, the threshold for acceptable voice quality is SIR equal to 18dB, for the 2G digital AMPS system (D-AMPS or IS-54/136), a threshold of 14 dB is deemed suitable, and for the GSM system, a range of 7–12 dB, depending on the study done, is suggested as the appropriate threshold, While, the probability of error in a digital system depends on the choice of this threshold as well. Wireless devices works reliably with SIR value of 0dBm or less [55]. The SIR value was calculated using the following equation:

$$\mathrm{SIR} = \sum_{\mathrm{i=1}}^{\mathrm{n}}[\frac{\mathrm{y_{i(inputsignal)}}}{\mathrm{y_{i(noise)}}}] \tag{17}$$

Where,

$\mathrm{y_{i(inputsignal)}}$ = Amplitude of input (Noisy signal)
$\mathrm{y_{i(noise)}}$ = Amplitude of noise removed through filtering.

4. RESULTS

4.1 ECG De-Noising Simulation Results

The simulation results for the ECG de-noising of different signals (104, 108, 109, 113, 117, 119, 209, 222, 230 and 232) have been carried out using Butterworth filter and Savitzky-Golay filter. The process uses equations 1 to 13 to carry out the simulation and the results are obtained in

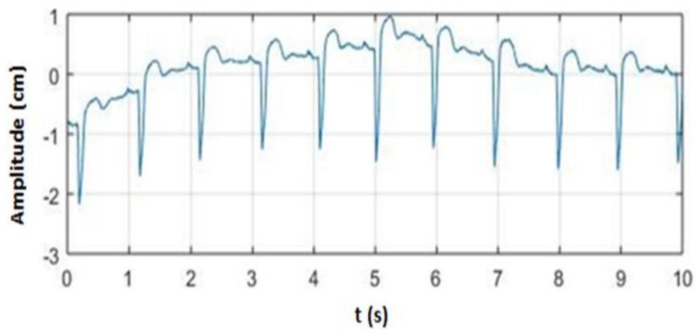

Fig. 1. Noisy signal 108 in time domain

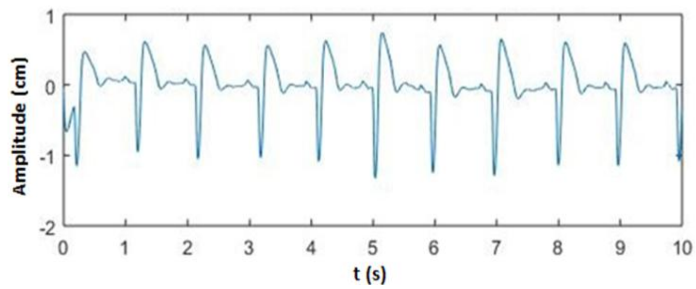

Fig. 2. De-noised signal 108 using Butterworth filter in time domain

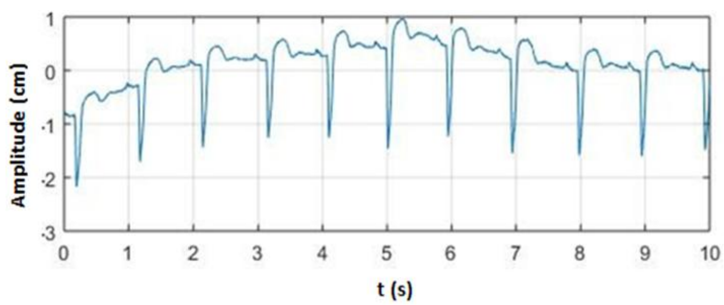

Fig. 3. De-noised signal 108 using S-G filter in time domain

both time and frequency domain representation. However, since the researcher cannot present all the simulated results, for the purpose of comparison, the results of signal (108) de-noised using Butterworth and Savitzky-Golay filters was randomly selected and presented in its time and frequency domains as shown in Figs. 1 to 6.

Fig. 1 shows the noisy signal 108 represented in its time domain, Fig. 2 is a representation of de-noised signal 108 using the Butterworth filter in its time domain, while Fig. 3 is a representation of de-noised signal 108 using the S-G filter in its time domain. Comparing Figs. 2 and 3 to Fig. 1 we see that the de-noised signal using Butterworth filter in Fig. 2 is sharp and clear but its original shape is not preserved, showing abnormally spiky waves which is quite unusual in morphology of the original waves. However, the de-noised signal using S-G filter in Figs. 3 maintains the original shape and morphology of the original signal after de-noising, showing that only the noise component was removed.

Fig. 4 is the noisy signal 108 represented in its frequency domain, Fig. 5 is a representation of de-noised signal 108 using the Butterworth filter in its frequency domain, while Fig. 6 is a representation of de-noised signal 108 using the S-G filter in its frequency domain. Comparing Figs. 5 and 6 to Fig. 4 we observe that the de-noised signal using Butterworth filter in Fig. 5 is sharp and clear, but produces an image signal along the negative axis. This is an indication of baseline drift a porous nature that may not be good for an ECG signal interpretation. However, the de-noised signal using the S-G filter in Fig. 6 is sharp, clear and maintains its original shape without baseline drift, though reduced in amplitude due to removal of the noise component of the signal, showing that the S-G filter is a good de-noising filter.

4.2 Performance Analysis

The performance analysis for the ECG signal de-noising of the different sampled ECG signals (104, 108, 109, 113, 117, 119, 209, 222, 230 and 232) using Butterworth filter and S-G filter has been carried out. The analysis for SNR, MSE, and SIR were carried our using equations 14 to 17 and are presented as shown in Table 1 to 3.

Table 1 presents the result of the performance analysis on SIR for the ten (10) sampled ECG signals de-noised using Butterworth and S-G filters. From Table 1 it can be observed that the SNR for Butterworth filter varies from 0.20dB to 4.17dB with a mean value of approximately 1.63dB. While for the S-G filter it varies from 22.17dB to 42.80dB with a mean value of approximately 32.78dB. The comparison of SNR for Butterworth and S-G filters for the de-noised ECG signals is as shown in Fig. 7.

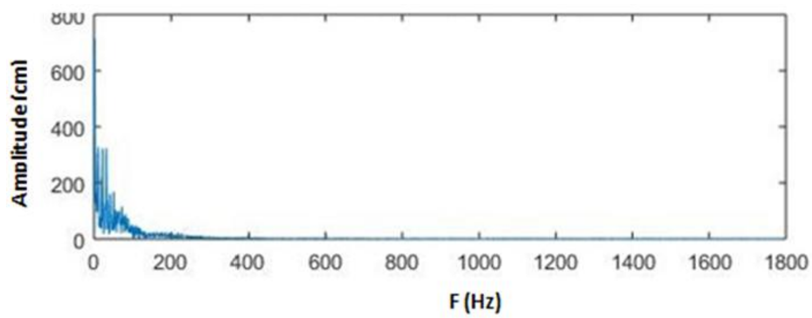

Fig. 4. Noisy signal 108 in frequency domain

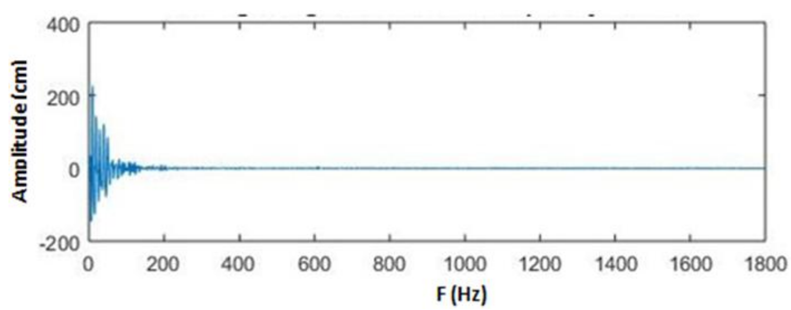

Fig. 5. De-noised signal 108 using Butterworth filter in frequency domain

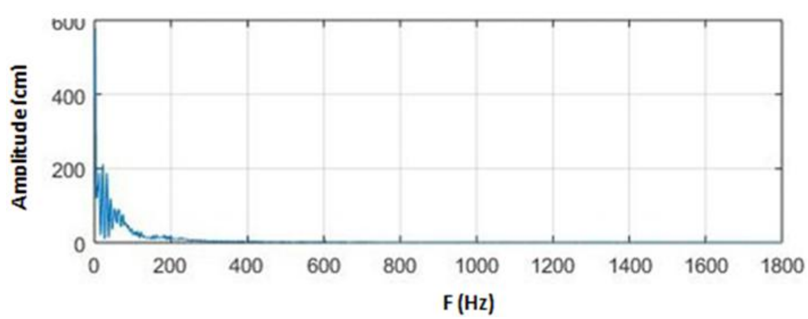

Fig. 6. De-noised signal 108 using S-G filter in frequency domain

Table 2 presents the result of the performance analysis on MSE for the ten (10) sampled ECG signals de-noised using Butterworth and S-G filters. From Table 2 it can be observed that the MSE for Butterworth filter varies from 0.0118 to 0.78279 with a mean value of approximately 0.2036. While for the S-G filter it varies from 0.00003 to 0.00034 with a mean value of approximately 0.0001. The comparison of MSE for Butterworth and S-G filters for the de-noised ECG signals is as shown in Fig.8.

Table 3 presents the result of the performance analysis on SIR for the ten (10) sampled ECG signals de-noised using Butterworth and S-G filters. From Table 3 it can be observed that the SIR for Butterworth filter varies from -3.738dB to 1.887dB with a mean value of approximately 0.259dB. While for the S-G filter it varies from -299.202dB to 81559.417dB with a mean value of approximately 1852.358dB. The comparison of SIR for Butterworth and S-G filters for the de-noised ECG signals is as shown in Fig. 9.

Table 1. SNR for de-noised ECG signal for Butterworth and S-G filters

S/NO	ECG SIGNAL	SNR (dB)	
		Butterworth	**S-G**
1	104	4.167281	23.506516
2	108	2.772084	36.051186
3	109	1.591261	35.516700
4	113	0.201191	31.530670
5	117	0.260447	42.452362
6	119	0.860306	42.804288
7	209	0.672459	22.170155
8	222	0.860959	26.506191
9	130	3.173209	35.120229
10	232	1.772571	32.139129
	Mean	1.633177	32.779743

Table 2. MSE for de-noised ECG signal for Butterworth and S-G filters

S/NO	ECG signal	MSE	
		Butterworth	**S-G**
1	104	0.029363	0.000342
2	108	0.135608	0.000064
3	109	0.176809	0.000072
4	113	0.076766	0.000057
5	117	0.723611	0.000044
6	119	0.782789	0.000050
7	209	0.011753	0.000083
8	222	0.031407	0.000086
9	130	0.038855	0.000025
10	232	0.028811	0.000026
	Mean	0.203577	0.000085

Table 3. SIR for de-noised ECG signal for Butterworth and S-G filters

S/NO	ECG signal	SIR (dB)	
		Butterworth	**S-G**
1	104	1.887332	-266.951652
2	108	-3.738311	-222.594120
3	109	-1.846677	3647.437893
4	113	0.980739	609.196198
5	117	0.707065	8159.417477
6	119	1.162270	1092.976430
7	209	1.107870	-299.202217
8	222	0.866190	22.577369
9	130	0.363691	217.857081
10	232	1.100660	5562.861507
	Mean	0.259083	1852.357597

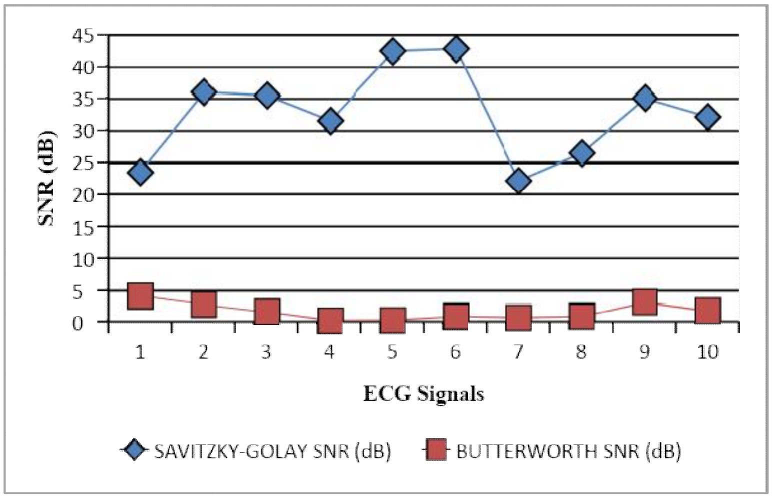

Fig. 7. Comparison of SNR for Butterworth and S-G filters for ECG de-noising

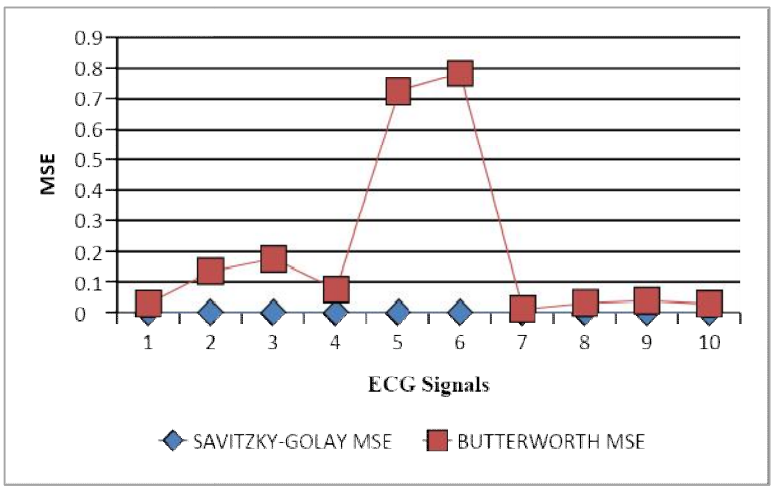

Fig. 8. Comparison of MSE for Butterworth and S-G filters for ECG de-noising

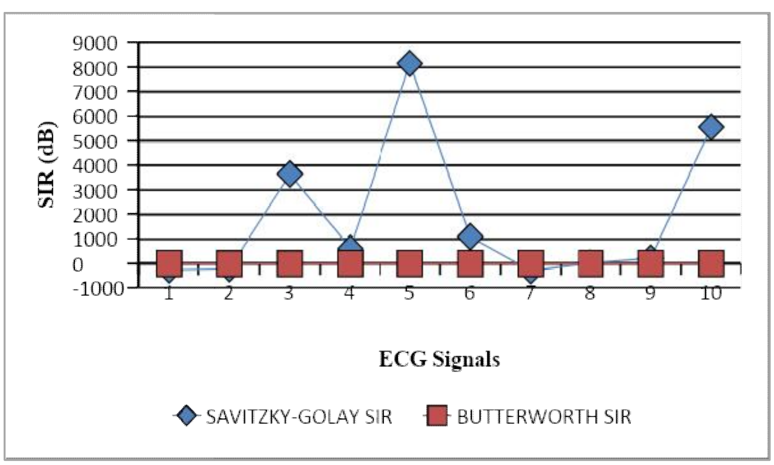

Fig. 9. Comparison of SNR for Butterworth and S-G filters for ECG de-noising

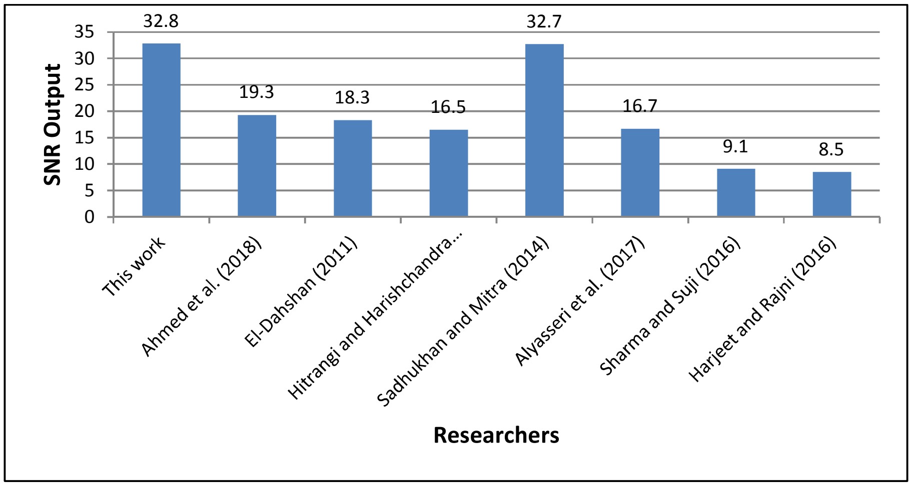

Fig. 10. Comparison of SNR output performance of this work with others

The results of SNR for this work are compared with the results of other researches with other methods: Ahmed et al. [31] who proposed the Genetic Algorithm (GA) with wavelet transform (WT) for de-noising of arrhythmia ECG signals, El-Dahshan [22] who proposed an effective hybrid scheme for the denoising of ECG signals corrupted by nonstationary noises using the GA and DWT, Hitrangi Sawant and Harishchandra [25] who proposed the ECG signal denoising using discrete wavelet transform, Sadhukhan and Mitra [24] who proposed an ECG noise reduction technique by suppressing the Fourier coefficient corresponding to the noise band, Alyasseri et al. [29] who worked on ECG denoising by using β-hill climbing algorithm with wavelet transform, Sharma and Suji [13] analyzed various window techniques for de-noising each ECG signal based on FIR filters, and Harjeet and Rajini [10] performed ECG signal de-noising using Savitzky-Golay filter and Discrete Wavelet Transform (DWT), as illustrated in the Fig. 10.

5. DISCUSSION

Comparing the simulation results of the Butterworth and S-G filters, it is observed that in the time domain the peak of the signal for the Butterworth filter is tempered with, showing abnormally spiky waves which is quite unusual in morphology of the original waves, this is an indication of noise. Even though Butterworth filter is a digital filter, it still falls under infinite impulse response (IIR) filter and so it is not linear. While the S-G filters tend to preserve the peak of the ECG signal and maintain the original morphology of the wave. This is because S-G filter is a finite impulse filter which worked by maintaining the signal power constant and only tries to decrease the noise power. This is in line with Krishnamurthy et al. [28]. Likewise in the frequency domain, Butterworth filter tends to create image signals in the negative axis which could also be a form of noise or baseline drift. While the S-G filter localizes the signal in the direction of the original signal after de-noising. This is a good indication that S-G filter performs better than Butterworth filter.

Findings from the performance analysis have revealed that the average SNR value after de-noising with Butterworth filter is approximately 1.63dB as against 32.78 dB for S-G filter. Since according to Net Spot [51] a ratio of 20-24dB is considered to be good, it implies that S-G filter takes care of the background noise better than Butterworth filter. This finding is not in line with the works of Krishnamurthy *et al.* [28] that obtain 27.32dB for Butterworth filter when he truncated IIR filters by multiplying them with a finite length window function to obtain finite impulse response filters whose frequency response is modified from that of the IIR filter and Harjeet and Rajini [10] that obtained an average value of 8.52dB using Discrete Wavelet Transform (DWT) even though they used S-G filter and carried out thresh-holding.

From the analysis of MSE, findings have revealed an average value of approximately 0.2036 for Butterworth filter as against 0.0001 for S-G filter which are both Ok. Since according to Bruner [52] smaller values imply smaller magnitudes of error, it implies that both filters have close fitting of de-noised signal line to the data point. This is in line with the findings of Harjeet and Rajini [10] that obtained 0.1201 for S-G filter and 0.0135 using DWT.

Finally, from the analysis of SIR, findings have revealed an average value of approximately 0.259 dB for Butterworth filter as against 1852.358 dB for S-G filter. According to Nnebe et al. [53] the higher the SIR the minimal the interference. Since the threshold value is 18dB, performance of S-G filter is regarding co-channel interference from other transmitters is better than that of Butterworth filter. This finding is similar to that of Rastogi and Mehra [16] that obtain an SIR value of 1.003 dB using the Butterworth filter.

From Tables 1 to 3 and Figs. 7 to 9, it is evident that S-G filter shows significant performance in terms of SNR, MSE and SIR considering all segments of ECG records than Butterworth filter, even though Butterworth filter show a good fit of the de-noised signal to the useful signal but that of S-G filter is better fitted and therefore a better filter for ECG de-noising.

6. CONCLUSION

The use of filters for de-noising has proven to be one of the solutions for a good and effective ECG signals for effective diagnosis and patient therapy on cardiac diseases. However, Comparative analysis of Butterworth filter and S-G filter for ECG signal de-noising using the Daubechies Wavelet is proposed. The main parameters concerned for the performance analysis of the filters are SNR, MSE, and SIR. Butterworth filter does not accurately provide useful information for the frequency morphology of the ECG signal; as such it is not robust to noisy signals and cannot be flexible in analysing the frequency varying structure of the ECG signal due to formation of image signals that could also be a form of noise and baseline drift. S-G filter shows good performance of de-noised ECG features in both time and frequency domains. The separation of noise, artifacts and baseline drift has proved robust. It is evident that S-G filter delivers better performance results as compared to Butterworth filter. Comparison of the result of the SNR of this work with other studies showed that the result of this work is better. Management of hospitals and cardiac health centres most understand the importance of ECG de-noising filters and the criteria for their selection for effective diagnosis and treatment of cardiac diseases.

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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