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Homam Hassan Jassim
BioMedical Department, College of Engineering, Thi_Qar University, Thi_Qar, Iraq,
homam.h.j.98@gmail.com

Dhuha Abdelabbas Kadim
Laser and Optoelectronics Engineering Department, University of Technology - Iraq, Baghdad, Iraq,
Duha92abd@gmail.com

Ahmed Abdelhadi
BioMedical Department, College of Engineering, Thi_Qar University, Thi_Qar, Iraq

Taif Alawsi
Laser and Optoelectronics Engineering Department, University of Technology - Iraq, Baghdad, Iraq,
taif.a.faisal@uotechnology.edu.iq

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ORIGINAL STUDY

The Employment of Filters in Electrocardiogram Signal Processing and their Applications

Homam Hassan Jassim [a], Dhuha Abdelabbas Kadim [b], Ahmed Abdelhadi [a], Taif Alawsi [b],*

[a] BioMedical Department, College of Engineering, Thi_Qar University, Thi_Qar, Iraq
[b] Laser and Optoelectronics Engineering Department, University of Technology - Iraq, Baghdad, Iraq

ABSTRACT

Filters are essential tools in the field of signal processing, they have been employed to control the signals and reduce or eliminate the noise associated with the signal. In this article, we will show the importance of filters in signal processing, especially in the field of biomedical engineering. As these filters will be applied to filter and remove noise from the electrocardiogram (ECG) signal, we will learn about some of the filters in this article.

Keywords: Filter, Biomedical engineering, ECG signal, Noise removal

1. Introduction

The Electrocardiogram (ECG) is an important bioelectrical signal, used by the cardiologist to diagnose various diseases and conditions associated with the heart and the state of the cardiac system [1]. ECG is a test that measures electrical activity of the heart with the help of electrodes placed on the surface of the body. The ECG is a graphic recording or display of time variant voltages produced by the myocardium during the cardiac cycle [2]. For the diagnosis a cardiologist also looks at the heart rate. The normal value of heart rate of an adult person lies in the range of 60 to 100 beats per minute (BPM) [3].

The ECG signal is usually damaged by noise during the recording process. Fig. 1 shows Original ECG signal. There are different types of noise present in the signal, the presence of which affects the signal properties and information. Fig. 1 shows Noisy ECG signal [4].

This may cause loss and / or damage of information for which it is difficult to notice and extract the parameters that we are interested in. Therefore, the characteristics and information of this signal must be preserved as we will use filters to filter the ECG signal. The most important of these filters are:

Savitzky and Golay gave a method for smoothing of data which is based on least-squares polynomial approximation. This involves fitting of a polynomial to an input samples set and then compute single point polynomial within the interval of approximation which means discrete convolution whose impulse response is fixed. Savitzky and Golay were trying to smooth noisy data of the chemical spectrum analyzers, and found out that least squares smoothing reduces noise and maintains the height and shape of waveform peaks. S-G filters can be used in smoothing noisy ECG data. Peak and shape preserving property of the S-G filters is has proved to be very efficient for accurate ECG processing [6].

The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the passband. It is also referred to as a maximally flat magnitude filter [7]. It was first described in 1930 by the British engineer and physicist Stephen Butterworth in his paper entitled

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* Corresponding author.
E-mail addresses: homam.h.j.98@gmail.com (H. Hassan Jassim), Duha92abd@gmail.com (D. Abdelabbas Kadim), taif.a.faisal@uotechnology.edu.iq (T. Alawsi).

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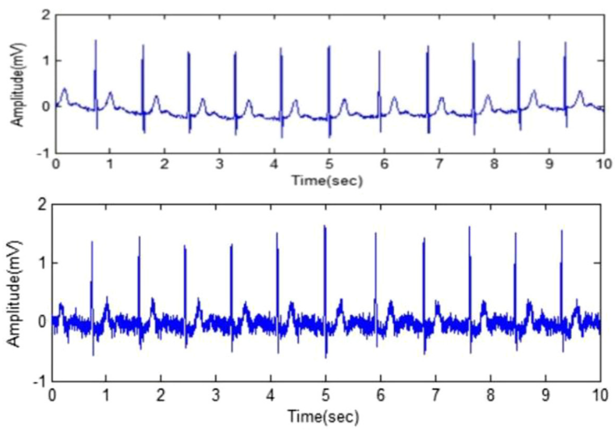

Fig. 1. (a) Original ECG signal (b) Noisy ECG signal [5].

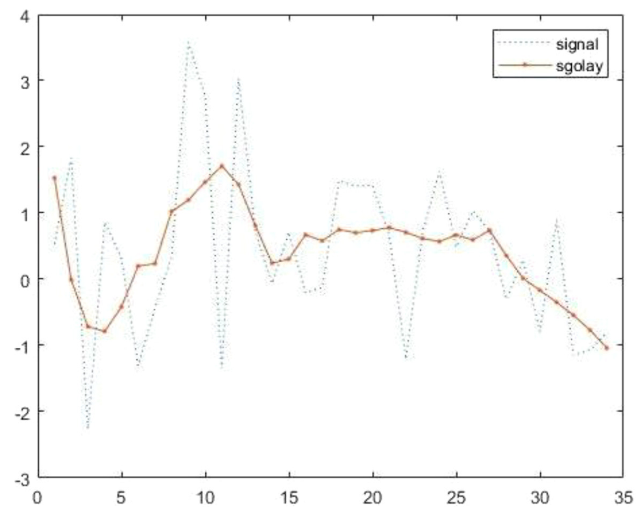

Fig. 2. The Savitaky-Golay filter.

"On the Theory of Filter Amplifiers" [8]. Median filter is a highly highly nonlinear filter (it re-orders the sample positions!). The output of the median filter at a position n is the median of the values that reside in the window scope; i.e., it's the value that resides in the middle when the samples are sorted in order. Hence median filtering requires sorting for each computation. This makes it quite slow as well [9]. In addition to the use of other filters such as the Gaussian filter, which is also an important filter in ECG filtering.

Recently, numerous active research effort was done in the field of ECG signal processing, some previous literature are as follows.

In 2020, Chen et al. [10] used Adaptive Periodic Segment Matrix to filter ECG signal from EMG artifact. The validation of proposed method is made by applying the algorithm to ECG records from four databases. Their results show that their proposed APSM-SVD method is effective for EMG artifacts removal and clean ECG signals extraction.

In 2021, Liu and Li [11] Used cooperative filtering of ECG segments to reduce the noise in the signal. ECG signals in the MIT-BIH database are denoised and used to other denoising methods. Their results show that the proposed method is effective.

In 2022, Dhas and Suchetha [12] adopted dual phase RLS filtering to enhance ECG signal. The proposed work provides an average output SNR of 14.07 dB, the correlation coefficient 0.980 at SNRi = 5 dB when evaluated on different ECG records.

In 2023, Thannoon and Hashim [13] used Recursive Least Square algorithm to remove the arifacts of ECG signal in adaptive filtering. Their results showed outperformance of proposed method to the conventional RLS algorithm in terms of signal-to-noise ratio (SNR), mean squared error (MSE), and convergence speed.

In 2024, Alla and Nayak [14] proposed adaptive filter to be used in ECG signal. Some experiments were done using real PhysioNet ECG signals contaminated with true BW, EM, MA, PLI, and additive white Gaussian noise (AWGN). The proposed RSA-based ANC demonstrates superiority over artificial bee colony (ABC) and flower pollination algorithm (FPA)-based ANC techniques, along with state-of-the-art ECG noise removal methods.

2. Filters

2.1. The Savitzky-Golay filter

A Savitzky-Golay filter is a digital filter that can be applied to a set of digital data points for the purpose of smoothing the data, that is, to increase the precision of the data without distorting the signal tendency, as shown in Fig. 2. This is achieved, in a process known as convolution, by fitting successive sub-sets of adjacent data points with a low-degree polynomial by the method of linear least squares. When the data points are equally spaced, an analytical solution to the least-squares equations can be found, in the form of a single set of "convolution coefficients" that can be applied to all data sub-sets, to give estimates of the smoothed signal, (or derivatives of the smoothed signal) at the central point of each sub-set. Abraham Savitzky and Marcel J. E. Golay who published tables of convolution coefficients for various polynomials and sub-set sizes in 1964 popularized the method, based on established mathematical procedures. Some errors in the tables have been corrected. The method has been extended for the treatment of 2- and 3-dimensional data [15].

Savitzky and Golay's paper is one of the most widely cited papers in the journal Analytical Chemistry and is classed by that journal as one of its "10 seminal papers" saying "it can be argued that the dawn of the computer-controlled analytical instrument can be traced to this article" [16, 17].

2.2. The moving average filter

A moving average filter is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. It is often used in technical analysis of financial data, like stock prices, returns or trading volumes. It is also used in economics to examine gross domestic product, employment or other macroeconomic time series [18]. An unweighted moving average filter is the simplest convolution filter. Each subset of the data set is fitted by a straight horizontal line. It was not included in the Savitzsky-Golay tables of convolution coefficients as all the coefficient values are simplyequal *to* $\frac{1}{m}$ [18].

A weighted average is an average that has multiplying factors to give different weights to data at different positions in the sample window. Mathematically, the weighted moving average is the convolution of the datum points with a fixed weighting function. One application is removing pixelisation from a digital graphical image. In technical analysis of financial data, a weighted moving average (WMA) has the specific meaning of weights that decrease in arithmetical progression. In an n-day WMA the latest day has weight n, the second latest $n-1$, etc., down to One.

$$\mathrm{WMA}_M = \frac{np_M + (n-1)p_{M-1} + \ldots + 2p_{(M-n+2)} + p_{(M-n+1)}}{n + (n-1) + \ldots + 2 + 1}$$

The denominator is a triangle number equal to $\frac{n(n+1)}{2}$. In the more general case, the denominator will always be the sum of the individual weights.

When calculating the WMA across successive values, the difference between the numerators of WMA_{M+1} and WMA_M *is* $np_{M+1} - P_M - \ldots - P_{M-n+1}$.

If we denote the sum $P_M + \ldots + P_{M-n+1}$ by Total_M, then:

$$\mathrm{Total}_{M+1} = \mathrm{Total}_M + p_{M+1} - p_{M-n+1}$$

$$\mathrm{Numerator}_{M+1} = \mathrm{Numerator}_M + np_{M+1} - \mathrm{Total}_M$$

$$\mathrm{WMA}_{M+1} = \frac{\mathrm{Numerator}_{M+1}}{n + (n-1) + \ldots + 2 + 1}$$

The graph at the right shows how the weights decrease, from highest weight for the most recent datum points, down to zero. It can be compared to the weights in the exponential moving average, which follows [19, 20].

2.3. The low pass Butterworth filter

The signal processing filter with a flat frequency response in the passband can be named as a Butterworth filter and also called as a very fixed size filter. As this type of filter is called the Butterworth filter. There are different types of Butterworth filters such as the Butterworth Low Pass Filter and the Digital Butterworth Filter. Here we will use the Butterworth low pass filter [21]. The frequency response of the Butterworth Filter approximation function is also often referred to as "maximally flat" (no ripples) response because the pass band is designed to have a frequency response which is as flat as mathematically possible from 0Hz (DC) until the cut-off frequency at −3 dB with no ripples. Higher frequencies beyond the cut-off point rolls-off down to zero in the stop band at 20 dB/decade or 6 dB/octave. This is because it has a "quality factor", "Q" of just 0.707. However, one main disadvantage of the Butterworth filter is that it achieves this pass band flatness at the expense of a wide transition band as the filter changes from the pass band to the stop band. It also has poor phase characteristics as well. The ideal frequency response, referred to as a "brick wall" filter, and the standard Butterworth approximations, for different filter orders are given below [22].

2.4. Gaussian filter

In electronics and signal processing, a Gaussian filter is a filter whose impulse response is a Gaussian function (or an approximation to it). Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. It is considered the ideal time domain filter, just as the sinc is the ideal frequency domain filter. These properties are important in areas such as oscilloscopes [2] and digital telecommunication systems. Mathematically, a Gaussian filter modifies the input signal by convolution with a Gaussian function; this transformation is also known as the Weierstrass transform [23].

2.5. Median filter

In signal processing, it is often desirable to be able to perform some kind of noise reduction on an image

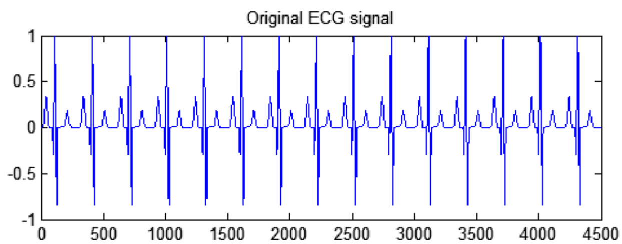

Fig. 3. Original ECG signal.

or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise [24].

3. Method

We first talked about the ECG signal and its significance, now we are applying all of the above by creating an ECG signal, and this must be determined sampling frequency (Fs) and then we use one of the task instructions in the Matlab, which is the ECG signal as shown below:

$$\mathrm{Fs} = \mathrm{p}$$

$$\mathrm{A} = \mathrm{ecg}(\mathrm{Fs})$$

Where the value of p represents the number of sampling frequency.

We take a certain number of samples or a number of cycles by inserting the ECG signal created in the into an array using a repmat command so that you will generate a minimum ECG signal. As shown below:

$$\mathrm{B} = \mathrm{repmat}(\mathrm{A}, \mathrm{m}, \mathrm{n})$$

Creates a large array B consisting of an m-by-n tiling of copies of the categorical array A. Fig. 3 represents the Original ECG signal.

We determine the value of Noise Coefficient, after which we multiply it by the ECG signal, and then we multiply it by all the data of the original signal by instructing the rand. As shown below:

$$\mathrm{r} = \mathrm{rand}([\mathrm{m}, \mathrm{n}]), \mathrm{returnsanm} - \mathrm{by} - \mathrm{nmatrix}$$

When the original ECG signal in this rand is compensated along the original signal, the resulting data is multiplied by the noise coefficient and then combined with the original signal and thus we have a

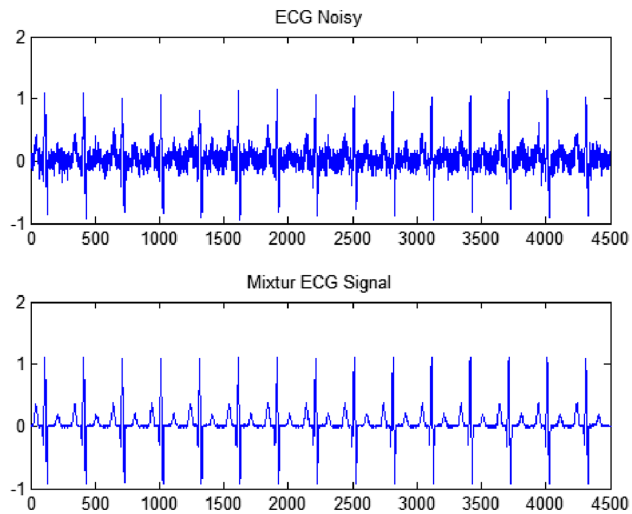

Fig. 4. ECG noisy and mixture ECG signal.

signal containing noise by the value of the input parameter. Fig. 4 shows the Original and Mixed ECG signal.

3.1. The Savitzky-Golay filter

The Savitzky-Golay filter with varying values of frame size and order is applied to the noisy synthetic ECG signal. It is ensured that the order of the polynomial does not exceed the frame size while varying the values iteratively. The poly- nomial order and frame size are varied from 2 to 10 and 15 to 25 in steps of 2 respectively. The filtered signal is obtained and evaluated over the spectrum of values. As the instruction that represents the mentioned filter in matlab is the following:

$$\mathrm{y} = \mathrm{sgolayfilt}(\mathrm{x}, \mathrm{order}, \mathrm{framelen})$$

Applies a Savitzky-Golay finite impulse response (FIR) smoothing filter of polynomial order order and frame length framelen to the data in vector x. If x is a matrix, then sgolayfilt operates on each column [20]. But the ECG reference used in this article is a matrix so it will apply to all columns. So x represents an ECG signal containing noise (input). Fig. 5 shows us this filter filtering the ECG signal.

3.2. The moving average filter

The moving average filter calculates the running average along the specified window. This is a relatively simple calculation compared to other filters. However, this will facilitate both signal and outliers. This causes the peak smoothing in the ECG signal to nearly a third of its size. The window length defines

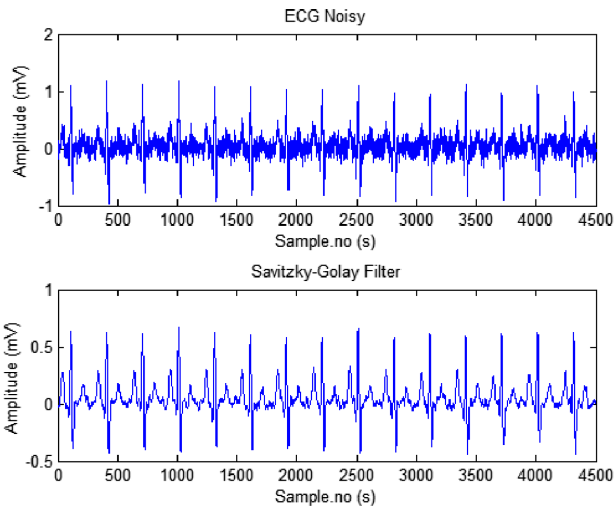

Fig. 5. ECG noisy signal and Savitzky-Golay filter.

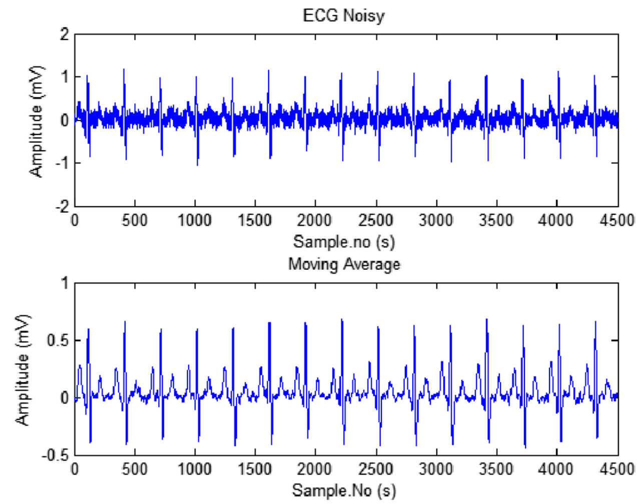

Fig. 6. ECG noisy signal and moving average filter.

the length of the data over which the algorithm computes the statistic. The window moves as the new data comes in. If the window is large, the statistic computed is closer to the stationary statistic of the data. For data that does not change rapidly, use a long window to get a smoother statistic. For data that changes fast, use a smaller window [22].

As the instruction that represents the mentioned filter in matlab is the following:

windowWidth = a

Where a is the number of new windows.

kernel = ones(windowWidth, 1)/windowWidth;
Output = filter(kernel, 1, x);

Where x denotes inputs (ECG signal contains noise) [23]. Fig. 6 shows us this filter filtering the ECG signal.

There is another type of moving average filters called the moving weighted window filter that filters out the ECG signal. After specifying the number of windows, we use the qausswin command to return an window-point Gaussian window in the column. window is a positive integer.

window = p

Where a is the number of new windows.

w = gausswin(window)

The coefficients of a Gaussian window are computed from the following equation.

$$w(n) = e^{-\frac{1}{2}\left(\alpha \frac{n}{\text{window}}\right)^2}$$

where - $\frac{(\text{window}-1)}{2} \leq n \leq \frac{(\text{window}-1)}{2}$ and α is inversely proportional to the standard deviation of a Gaussian random variable. The exact correspondence with the standard deviation, σ, of a Gaussian probability density function is $\sigma = \frac{\text{window}}{2\alpha}$

3.3. The low pass Butterworth filter

Filtering of ECG signal: Filtering of any signal is done to remove any type of noise or distortion present in the signal. Here we are using Butterworth low pass filter to remove the noise. We are not using the Butterworth high pass filter because it creates more distortion in our signal after applying it.

As the instruction that represents the mentioned filter in matlab is the following:

[B, A]= butter(N, Fc $*$ 2/Fs,′ low′)

Whereas the value of N represents the arrangement of the filter whereas 'low' means the type of filter used here is low pass Butterworth, and (fNorm) is the product of the cutoff frequency (Fc) by 2 divided by sampling frequency (Fs) of the ECG signal [24].

Now we are filtering the low pass butterwort filter through the following:

Output = filter(B, A, data)

Whereas, data represents an ECG signal containing noise (input). Fig. 7 shows us this filter filtering the ECG signal.

3.4. Gaussian filter

Gaussian filter shown in Fig. 8 is one of the crucial important for both the theory and application com-

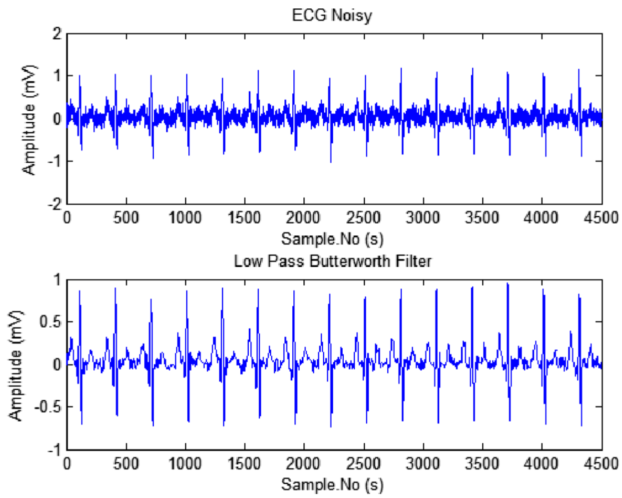

Fig. 7. ECG noisy signal and low pass Butterworth filter.

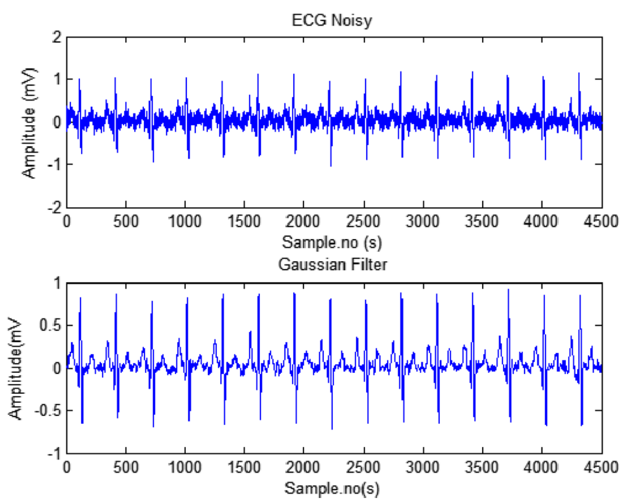

Fig. 8. ECG noisy signal and Gaussian filter.

pared to other linear filters. It can be represented in MATLAB by the following instruction:

$$y = \mathrm{filter}(h, 1, x)$$

Where x represents the signal containing noise and h represents next:

$$h = \mathrm{normpdf}(-\mathrm{window} : \mathrm{window}, 0,$$

$$\mathrm{fix}((2 * \mathrm{window} + 1)/6)$$

$$\mathrm{window} = \mathrm{number}$$

3.5. Median filter

Median filter is a highly highly nonlinear filter (it re-orders the sample positions!). The output of the median filter at a position n is the median

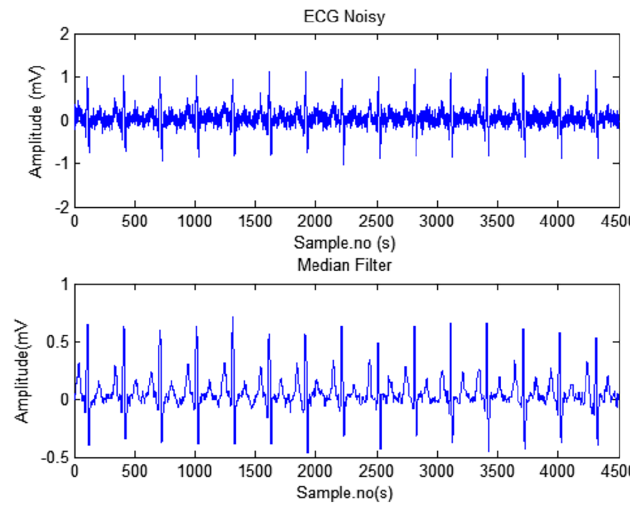

Fig. 9. ECG noisy signal and The Median filter.

of the values that reside in the window scope; i.e., it's the value that resides in the middle when the samples are sorted in order. Hence median filtering requires sorting for each computation. Median filter is mainly used for speckle or salt and pepper noise removal, in essence these are local noise samples whose frequency domain filtering is not possible without degrading the whole signal. Such local (in time) peaks will have wide band frequency spectrums which inhibit frequency domain attacks to remove them, therefore, leaving only the time domain (or time-frequency domain) approaches possible. As shown in Fig. 9.

Median filter has a tendency to preserve edges, therefore quite preferred in certain image enhancement operations. However it also has the side effect of washed out results (texture details are lost and only strong edges remain) which indicates that their use should be performed with care. In principle, the longer the window size, the stronger will be the washed out effect. So it's customary to use as short as possible window sizes (unless otherwise dictated by the particular application) [25].

It can be represented in MATLAB by the following instruction:

$$y = \mathrm{medfilt1}\,(x, \mathrm{window})$$

Where x represents the signal containing noise and window represents the number of windows [25].

$$\mathrm{window} = \mathrm{No}$$

This is a filter that makes possible for the elimination of a divergent value by changing the divergent value in a finite series with the medium value in the same series [22]. When it is of two dimensions, the

Fig. 10. ECG signal from detection to processing.

Table 1. Application of different filters on ECG input signal and measuring the SNR.

Input signal	Filters	SNR
300ECG	Savitzky-Golay	0.5019
	Moving Average	0.5018
	Moving Weighted Window	0.6654
	Low Pass Butterworth	0.5784
	Gaussian	0.7417
	Median	0.5401
	FIR	0.5510

MF for images would be developed as follows:

$$m(k) = med\, w(k)$$
$$= med\{x_{-n}(k), \ldots, x_{-1}(k), x_0(k), x_1(k), \ldots, x_n(k)\}$$

4. Results

As shown in previous papers on the ECG signal, the amount of interference the signal contains, and how to treat it through filters. We also learned about some filters, their importance and their role in processing this signal, so the diagram below represents the process that was completely performed on the ECG signal, as shown in Fig. 10.

We take SNR and define it to know the importance of each filter by giving the amount of filtering to a signal.

SNR:- Signal-to-noise ratio (abbreviated SNR or S/N) is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. SNR higher than 1 or greater than 0 dB indicates more signal power than noise power. While SNR is commonly quoted for electrical signals, it can be applied to any form of signal [26].

The expression for calculating SNR is as follows:

$$\mathrm{SNR} = 10 \times \log \frac{(\Sigma_0^{(N-1)}(Xs(n))^2)}{(\Sigma_0^{(N-1)}(Xs(n) - Xr(n))^2)}$$

Here the Table 1 gives the SNR values for these filters used in the article.

The Figs. 11 and 12 show the result of the signal made by these filters.

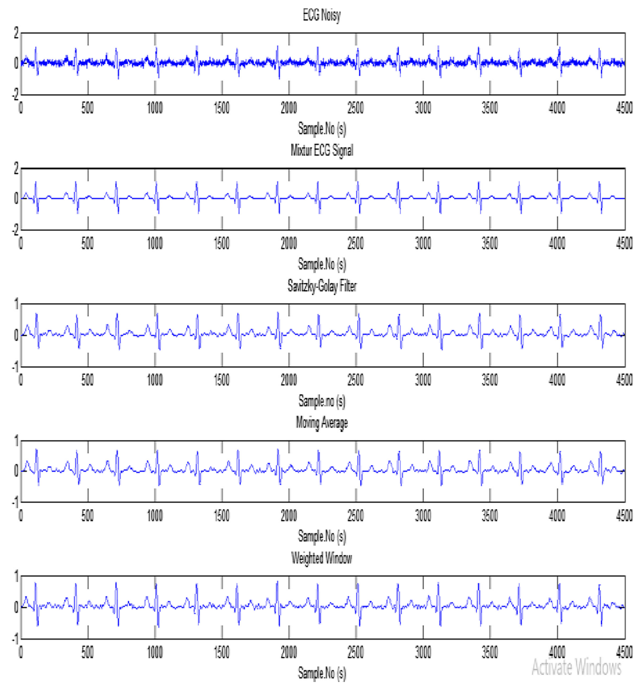

Fig. 11. The output of filtering the first set of filters.

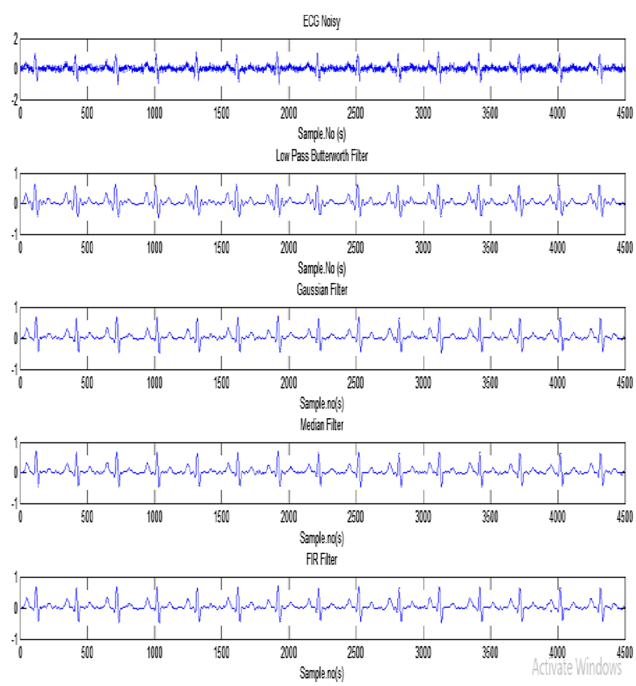

Fig. 12. The output of the second set of filters filter.

5. Conclusion

This paper introduces a technology to pre-process an ECG signal using the Savitzky-Golay filter and the Moving medium filter used to soften data by increasing the signal-to-noise ratio. The proposed Savitzky-Golay filtering algorithm has been shown to achieve better smoothing compared to the Moving-average filter. Simulation results show that the technique suggested in this paper can improve pre-treatment of the ECG signal. Simulation and quantitative evaluation results demonstrate that Savitzky-Golay and Moving-Medium filter facilitate signal. The Butterworth filter used, effectively remove noise from the corrupted ECG signal. After finding out all the features and comparing it with the standard values we can decide that the person is normal or abnormal. A MATLAB based analytical method for feature extraction and disease diagnosis is used.

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