Reduction of Noises In ECG Signal by Various Filters

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Abstract

In this work, different type of filters are proposed for improving the removal of noise in ECG signals. This type of filtering procedure is applied to the Several ECG patient signals. That ECG signals are collected from MIT-BIH database. The ECG signal from MIT-BIH arrhythmia database may contain artifacts, noise and baseline wanders. Therefore it is necessary to denoise the ECG signal to remove all these unwanted parts of the signal. The noise filtering progress is applied to the 30 ECG signals, that the filtering process are Median filter, Finite impulse response filter, Butterworth filter, Gaussian filter. Two type of performance metrics are evaluated for this noise removal technique. The metrics are Mean Square error, Peak Signal to Noise Ratio.

Keywords: *ECG, MIT-BIH Database, Median filter, FIR filter, Gaussian filter, Butterworth filter.*

1. Introduction:

The electrocardiogram (ECG) is one of the bio-electric signals and it is used to take the electrical activities of the heart. The signal of the ECG is characterizes by the PQRS Waveform. This type of bioelectrical signal mostly used in clinical side to identified the heart diseases in the Patients. The surface electrodes are used to measure the ECG signal. Some time noises are produced through this surface electrode, that the electrodes are not placed properly in the patient. Some of the steps to remove the artifact basically they are

- Check the patient skin, carry out and preparing good skin for the patient.
- Check the electrode gel.
- In the time of checking the patient should be warm and not to speak and move.
- Check the chest lead that is placed in proper position or not. If it is not placed properly means it leads to false diagnosis of infarction.
- Check the Patient cable connection to the ECG device

These are some of the points that lead to produce noise in the ECG signal.

By this type of interference some type of noises are present in the ECG signal. These types of noises are baseline wander, Power line interference, motion artifacts, electrode contact, and instrument noise [1]. To remove these type of noises in the ECG signal with the help of novel filters in the time of processing the method of preprocessing.

In this paper that the preprocessing method provides the removal of noise in the ECG signal and provides the very effective way to detect the heart diseases in the patient. The base line wander noises are produced by the amplitude and frequency variations in the ECG signal [1]. It is observed that the 50% of base line noises are present in the amplitude of the ECG signal. Another most important type on noise, which mostly appeared in ECG signal, is power line interference and it is caused by the 60HZ in the sinusoidal and its harmonics. During signal measurement some type on noises are detected that are electrode motion and muscle contraction [2]. Low-pass filter and high-pass filters are the usual filters to remove the noise in the ECG signal. But these types of filters produce artifacts on the QRS complex [4] and some type of filter banks also produces these artifacts [5, 6]. Some type of filters algorithm together with the ECG signal modelling used to remove the noise reduction in ECG signal [7, 8, and 9]. Extended Kalman filters techniques are used to remove the noise in ECG signal [7]. Some of the techniques such as mean shift algorithm [8] state vectors with time delay [10] and empirical mode decomposition [11] are used for ECG signal noise reduction.

Modern techniques such as Principle Component Analysis, Neural Network, and Wavelet transform are used to remove the noise in the ECG signal, especially it remove the high frequency from their wave it have a disadvantage that their bandwidth is not constant. [12, 13, 14]. Another one method to remove the baseline wanders by using wavelet based cascaded adaptive filter. Here they introduce the energy ratio; if the energy ratio is greater than the given threshold then the noise removal is taken by cubic spline estimation otherwise it must be filtered by discrete Meyer wavelet filter and the cubic spline estimation [15].

ECG signal are collected from the MIT-BIH Arrhythmia database. This database includes 48 half-hour recordings of two leads of ECG signals. These ECG signals are recorded at a sampling frequency of 360 Hz with 11 bit resolution over a 10mv range [3].

Several method has developed to remove the noise in the ECG signal depend on filter banks [16-21] they are principal component analysis (PCA), independent component analysis (ICA), neural networks (NNs), adaptive filtering, empirical mode decomposition EMD, Wavelet Transform.

2. Type of filters

Median filter:

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 MF for images would be developed as follows

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

Gaussian filter:

Gaussian filter is one of the crucial important for both the theory and application compared to other linear filters. In two dimensional this filter is given by

$$g_\sigma(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2}{2\sigma^2}}. \quad (2)$$

In this equation σ denotes the scale level and it control the filter width,

So the denoised image

$$\tilde{u} = g_\sigma * Z. \quad (3)$$

Then the denoising error can be decomposed as

$$\|\tilde{u} - \bar{u}\|_2 \leq \|g_\sigma * \bar{u} - \bar{u}\|_2 + \|g_\sigma * n\|_2, \quad (4)$$

Here the σ controls the tradeoff between removing noise.

Gaussian filter is remarkably associated with the linear heat diffusion equation:

$$u_t(x,t) = \frac{1}{2}\Delta(x,t) = \frac{1}{2}\left(u_{x_1x_1} + u_{x_2x_2}\right) \quad (5)$$

$$u(x,t) = Z(x) \quad (6)$$

Its solution is

$$u(x,t) = g_{\sqrt{t}} * z(x). \quad (7)$$

From this relation, the heat equation also suggests a convenient way to calculate the Gaussian filter. For digital image

$$u_{i,j}^n = u(ih, jh, n\tau) \quad (8)$$

Denote the digital sample of a continuous image sequence $u(x_1, x_2, t)$on a Cartesian grid of resolution h with temporal sampling rateτ. Under the central difference scheme, the forward Euler scheme in the temporal direction leads to the digital Gaussian filtering formula.

$$u_{i,j}^{n+1} = \lambda\left(u_{i+1,j}^n + u_{i-1,j}^n + u_{i,j+1}^n + u_{i,j-1}^n\right) + (1-4\lambda)u_{i,j}^n \quad (9)$$

Where$\lambda = \frac{\tau}{2h^2}$. For stability reason it is required that $\lambda \leq \frac{1}{4}$

The key issue arising from diffusion-based denoising schemes is the problem of optimal stopping time, that is, to decide when to stop the process to achieve a well-balanced performance of suppressing the noise while retaining the fidelity of the target signal. Without termination at certain finite time T, by the conservation law of adiabatic diffusion, as $t \to \infty, u(x,t)$ will go to the mean of z over the whole image domain. A general way of choosing optimal stopping time usually depends on a cost or risk function, which properly defined to faithfully reflect human or machine visual perception.

Low-Pass Butterworth Filter:

Assume an Nth-order transfer function of analog low-pass Butterworth prototype is

$$H(s) = \frac{1}{\sum_{n=0}^{N} A_n s^n} \quad (10)$$

Through the mapping between the analog and digital domain, its corresponding digital low-pass and high-pass filters are in the form

$$H(Z) = \frac{(1 + b_{01}Z^{-1})}{(1 + a_{01}Z^{-1})} \frac{(1 + b_{11}Z^{-1} + b_{12}Z^{-2})}{(1 + a_{11}Z^{-1} + a_{12}Z^{-2})} \ldots \ldots \frac{(1+b_{K1}Z^{-1}+b_{K2}Z^{-2})}{(1+a_{K1}Z^{-1}+a_{K2}Z^{-2})} \quad K = \left\lfloor\frac{N}{2}\right\rfloor \quad (11)$$

Where $b_{01} = a_{01} = 0$, if N is an even integer.

K is the largest integer not greater than $\frac{N}{2}$

For designing digital band-pass and band-pass filters, s is quadratic in Z, so the mapping leads to a 2Nth-order transfer function in Z given by

$$H(Z) = \frac{(1+b_{01}Z^{-1}+b_{02}Z^{-1})}{(1+a_{01}Z^{-1}+a_{02}Z^{-1})} \frac{(1 + b_{11}Z^{-1} + b_{12}Z^{-2} + b_{13}Z^{-3} + b_{14}Z^{-4})}{(1 + a_{11}Z^{-1} + a_{12}Z^{-2} + a_{13}Z^{-3} + a_{14}Z^{-4})} \ldots \frac{(1+b_{K1}Z^{-1}+b_{K2}Z^{-2}+b_{K3}Z^{-3}+b_{K4}Z^{-4})}{(1+a_{K1}Z^{-1}+a_{K2}Z^{-2}+a_{K3}Z^{-3}+a_{K4}Z^{-4})}, \quad K = \left\lfloor\frac{N}{2}\right\rfloor \quad (12)\ (13)$$

Where$b_{01} = b_{02} = a_{01} = a_{02} = 0$, if N is an even integer.

The transfer function of digital filters can be split into a gain factor and a filter transfer function itself as

$$H(Z) = GH'(Z) \tag{14}$$

Where

$$H'(Z) = \frac{N(Z)}{D(Z)} \tag{15}$$

Window based FIR Filter:

In this method start with the desired frequency response specification $H_d(w)$ and the corresponding unit sample response $h_d(n)$ is determined using inverse Fourier transform. The relation between $H_d(w)$ and $h_d(n)$ is as follows:

$$H_d(w) = \sum_{i=0}^{\infty} h_d(n)e^{-jwn} \tag{16}$$

$$h_d(n) = \int_{-\pi}^{\pi} H_d(w)e^{jwn}\,dw \tag{17}$$

The impulse response $h_d(n)$ obtained from the above equation is of infinite duration. So, it is truncated at some point, say n=M-1 to yield an FIR filter of length M (i.e. 0 to M-1). This truncation of $h_d(n)$ to length M-1 is done by multiplying $h_d(n)$ with an window. Here the design is explained by considering the "rectangular window", define as

$$w(n) = \begin{cases} 1 & n = 0,1,2 \ldots\ldots M-1 \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

Thus, the impulse response of the FIR filter becomes

$$h(n) = h_d(n)w(n)$$
$$= \begin{cases} h_d(n) & n = 0,1,2 \ldots. M-1 \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

Now the multiplication of the widow function $w(n)$with $h_d(n)$ is equivalent to convolution of $H_d(w)$with $W(w)$, where $W(w)$the frequency domain representation of the window function is

$$W(\omega) = \sum_{i=0}^{\infty} w(n)e^{-jwn} \tag{20}$$

Thus the convolution of $H_d(w)$with $W(\omega)$ yields the frequency response of the truncated FIR filter $H(\omega)$

3. Experimental results

Simulation results are carried from the MIT –BIH arrhythmia database to remove the noise in the ECG signal. MIT BIH ECG signals are illustrated by three files they are (.hea) denoted as header file, (.dat) denoted as binary file and (.atr) denoted as binary annotation file. Comprehensive information of ECG signal was present in this header file, that what type of lead used for the patient and number of lead used for diagnosing and their sampling frequency and patient history. In binary file what type of format that the signal is stored. ECG beat information is stored in binary annotation file. For this experimental result consider the ECG signals numbered as 100, 103, 104, 105, 106, 115 likewise totally 29 patients ECG signals are picked from the MIT-BIH database. Then applied different kind of filters to these signals to remove the different noises are baseline wander, power line interference, muscle artifact noise, and electrode motion artifact noise and compared the filters output by performance metrics are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR).

Performance metrics:

Removal of noise in the ECG signal using Median filter, Finite impulse response filter, Gaussian filter, Butterworth filter. For this performance some type of metrics has taken placed in this paper and compared them to show the result of best performance for noise removal in the ECG signal. Compare the type of filters by MSE, PSNR.

Let us take

$$x = \text{double}(\text{input image})$$
$$y = \text{double}(\text{filtered image})$$
$$z = \text{abs}(x - y)$$

$$MSE = \sqrt{\text{mean}(\text{mean}(z.\hat{}2)))} \tag{21}$$

MSE is denoted as Mean Square Error. That the largest value of MSE means that the ECG signal is poor quality

.

$$PSNR = 20 * \log10\left(\frac{255}{\sqrt{MSE}}\right) \tag{22}$$

PSNR is denoted as Peak signal to Noise Ratio. PSNR is opposite to MSE, that if the small value of PSNR means that the removal of noise in the ECG signal doesn't provide better result.

Table I

Comparison of filters

Input signal	Filters	MSE	PSNR
M107ECG	Median	**0.0637**	**72.0461**
	FIR	0.3498	57.2546
	Gaussian	0.1271	66.0498
	Butterworth	0.0895	69.0940
M111ECG	Median	**0.0345**	**77.3629**
	FIR	0.1385	65.3016
	Gaussian	0.0782	70.2647
	Butterworth	0.0477	74.5604
M209ECG	Median	0.0857	69.4673
	FIR	0.1822	62.9203
	Gaussian	**0.0530**	**73.6532**
	Butterworth	0.1103	67.2815
M217ECG	Median	**0.0601**	**72.5511**
	FIR	0.2570	59.9324
	Gaussian	0.0986	68.2558
	Butterworth	0.0703	71.1978

The above table gives the comparison of MSE, PSNR for four types of filters for M107ECG, M111ECG, M209ECG, M217ECG signal from MIT-BIH database. From the comparison table it is clearly observed that the median filter and Gaussian filter gives better result compared to other filters in this paper. The better results given by median and Gaussian filters are shown in table V as a block letter.

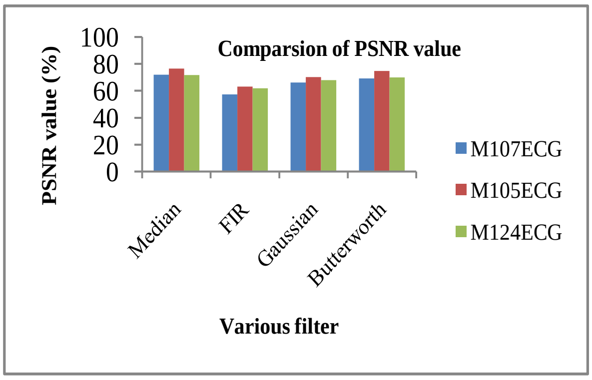
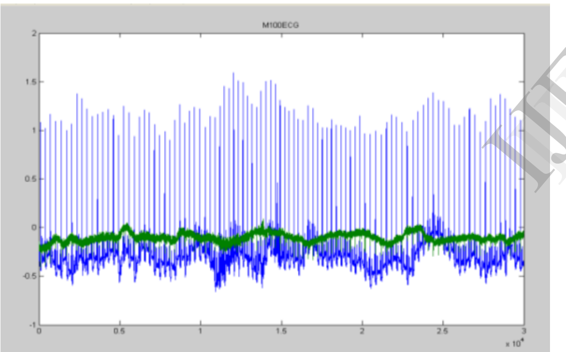
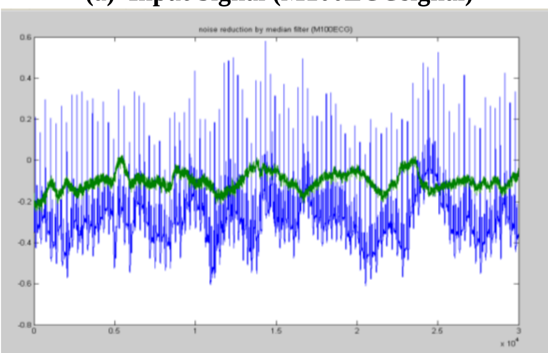


Figure 1 Comparison of PSNR value

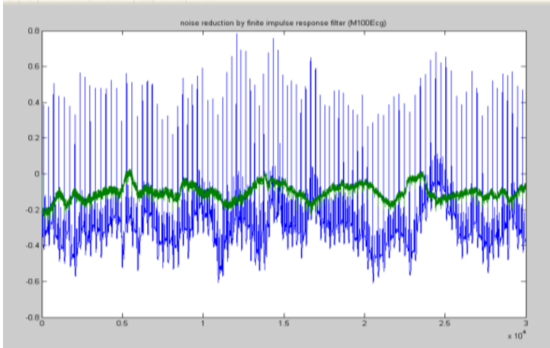
The comparison of PSNR value for various filters for the M100ECG, M105ECG and M124ECG signal from MIT BIH database is shown in figure 3. From the above graph it is noted that the median filters provides better result compared to other filter such as FIR filter, Gaussian filter, and Butterworth filter.



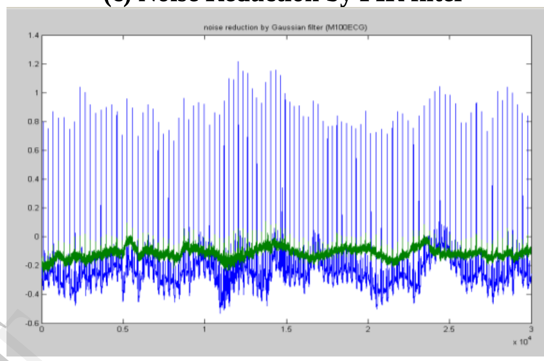
(a) Input Signal (M100ECGsignal)



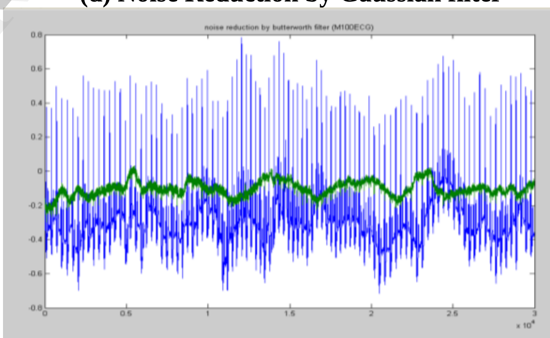
(b) Noise reduction by Median filter



(c) Noise Reduction by FIR filter



(d) Noise Reduction by Gaussian filter



(e) Noise Reduction by Butterworth filter
Figure 2 Results of removal of noise in M100ECG signal using different filters

Comparison of signal M100ECG have taken and it is shown in above figure. The simulation results of graph have shown in figure 1 shows that the different type of filters is able to reduce the noise in ECG signal. To removal of noise in ECG signal of M100ECG is shown in figure 1, that the input signal is shown in figure 1(a), noise reduction in M100ECG by median filter is shown in figure 1(b), noise reduction by finite impulse response filter is shown in figure 1(c), noise reduction by Gaussian filter is shown in figure 1(d) and noise reduction by butterwort filter is shown in figure 1(e).

4. Conclusion

ECG preprocessing is most important one in their process. In this paper conducted to remove the noise in the ECG signal. First the removal of noise is very helpful to identify the correct ECG signal in medical field. Because in clinical field, ECG signal is mostly used to identify the patient heart diseases. That the noises are obtained by various problems, due to instrument error, electrode contacts, motion artifacts, power line interference. In this paper, ECG signals are collected from MIT-BIH database. Totally 30 ECG signals are obtained from this database. To remove the noise in the ECG signals are done four type of filter they are Median filter, FIR filter, Gaussian filter, Butterworth filter. Then the performances are evaluated by PSNR, MSE. Table I gives comparison between these four filters. Simulation results of median filter approach can efficiently remove the noise in the ECG signal and give best result compared to other approaches. The performance of PSNR for all filters is shown in figure 2. Therefore overall performance of Median filter gives the best performance followed by Gaussian filter.

5. References

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