



REMOVING BASELINE WANDER FROM ECG SIGNAL USING WAVELET TRANSFORM

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Abstract: Electrocardiogram (ECG) signal is the representation of electrical activity generated by heart muscles, which is primarily utilized to detect cardiac abnormalities. Due to the sensitive nature of ECG, its important features are affected by different noises and create problems for diagnosis. This study proposes biorthogonal wavelet family by investigating different wavelet families to reduce baseline wander from the ECG signal. The proposed approach performance is compared to adaptive normalized least-mean-square (NLMS) and notch filters. Different performance parameters, such as amplitude spectrum, magnitude squared coherence (MSC), and power spectral density (PSD) has been evaluated. Signal-to-noise ratio (SNR), percentage root-mean-square difference (PRD), mean-square-error (MSE), normalized mean-square-error (NMSE), root mean-square-error (RMSE), and normalized root mean-square-error (NRMSE) performance parameters are calculated as well. The SNR values of the reconstructed ECG signal are -0.0046 dB and 1.6122 dB for notch and adaptive NLMS filters, respectively, which are lower than that of 8.0464 dB for the biorthogonal wavelet transform. Similarly, the MSC values are 0.091903 and 0.44522 after notch and adaptive NLMS filtrations, respectively, which are lower than those of 0.8913 after wavelet filtration. Also, the PSD value for the wavelet transform is -9.317 dB/Hz, which is better than that of adaptive NLMS (-6.788 dB/Hz) and notch (-6.669 dB/Hz) filters. Therefore, the analysis based on performance parameters has justified that proposed biorthogonal wavelet family represent better performance for reducing baseline wander from the ECG signal than adaptive NLMS and notch filters.

Keywords: ECG signal, baseline wander, wavelet transform, SNRimp, MSE, MSC

Introduction

Electrocardiogram (ECG) signal is an essential tool to diagnose and evaluate different heart diseases in the clinical environment. Generally, the P, QRS complex and T- waves related to each beat are used to characterize the ECG signal. These characteristics may be varied in duration and amplitude. The analysis of this morphology variation of ECG signal facilitates the clinician to diagnose various cardiac abnormalities. In the clinical setting during recording and transmission, various types of (low and high frequency) noises such as baseline wander, 50 Hz power line and electromyogram noise etc. can affect original ECG signal (Maggio, Bonomini, Leber, & Arini, 2012). Among those noises, below 1 Hz baseline wander noise is considered as most critical because it falls into the ECG signal band and significantly corrupts the low-frequency region of the original ECG signal. Therefore, the baseline wander removal from the ECG signal has been very essential.

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Various Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters are utilized for denoising ECG signal (Das & Chakraborty, 2017; Saxena, Upadhyaya, Gupta, & Sharma, 2018; Singh, Ayub, & Saini, 2013). High pass filter can be applied to eliminate the low-frequency interference from ECG signal (Rahman, Milu, Anjum, Khanam, & Ahmad, 2017). But the high pass filter removes the lower portion of the ECG signal along with noise. In addition, the traditional IIR notch filter (Rahmatillah & Ataulkarim, 2017) with a fixed coefficient can also be used to reduce any certain noise frequency from the ECG signal. But, it is difficult to apply this type of notch filter, because it has fixed coefficients and the ECG signal has a non-stationary nature. So, when this type of notch filter removes below 1 Hz baseline wander noise, it also removes a narrow frequency of ECG signal around this noise. For this reason, although the noise is being eliminated, some significant frequency content of the original signal is also removed with noise. Sometimes the ringing effect is introduced in the notch filtered output signal (Gokhale, 2012).

On the other hand, it is reported by the several studies that the adaptive filter removes the baseline wander more significantly from the noisy ECG signal (Chandrakar & Kowar, 2012; Qureshi, Rizvi, Musavi, Khan, & Khurshid, 2017; Reddy, Rahman, Sangeetha, & Sudha, 2011). Because the adaptive filter makes, least-mean-square of error signal through self-adjusting its transfer function based on an optimizing algorithm (least-mean-square (LMS) algorithm). But when the step size of the LMS algorithm become large its coefficients fluctuate widely and eventually become unstable. Therefore, the LMS algorithm has a gradient noise amplification issue for large step size, which may be solved by normalizing the step size. After normalizing the step size of the LMS algorithm, it is referred to as the Normalized LMS (NLMS) algorithm. It has been reported that the adaptive NLMS filter performance for denoising ECG signal including baseline wander is better than the adaptive LMS filter (Biswas, Das, Debnath, & Oishee, 2014; Biswas & Maniruzzaman, 2014; Maniruzzaman, Billah, Biswas, & Gain, 2012). But sometimes if the step size of the adaptive filter is not adjusted properly it may also cause stability and computational complexity issues.

As the ECG is nonstationary, both time and frequency domains should demonstrate sufficient resolution during the analysis of this signal. In view of this aspect, currently, the wavelet transform has become much more popular for denoising ECG signal (Belgurzi & Elshafiey, 2017; Oliveira, Duarte, Abreu, & Vieira Filho, 2018). The wavelet transform is a technique that usually provides more time-frequency information's in the time-frequency plane compared to the Fourier transform. During signal decomposition, wavelet transform has the ability to decompose a signal as elementary building blocks in both time-frequency planes, which makes it unique from other techniques. The wavelet transform usually prefers a short window at high frequencies and long window at low frequencies to ensure sufficient time and frequency resolution at high and low-frequency portion of the signal, respectively. On the other hand, the dimension and size of the output signal are about the same as the input signal, which gives the wavelet transform very powerful potential in ECG signal denoising.

In the current study, wavelet families (Biswas & Maniruzzaman, 2015; Gokhale, 2012) are employed to reduce baseline wander from ECG signal that can be utilized in the hospital environment to improve the quality of care for the critical cardiac patient. The main contribution of this study based on finding the suitable wavelet family, thresholding rule and decomposition level for denoising real ECG signal. With the help of this selected wavelet family, the clinicians can accurately monitor the life-threatening patient by reducing baseline wander and other noises from the ECG signal. The proposed denoising technique has been analyzed using 45 real ECG records and different performance parameters. The effectiveness of this proposed denoising approach has been verified in the results and discussion section, which clearly showed the good quality of denoised ECG signal with highest Signal-to-noise ratio improvement (SNRimp) than the traditional notch (Rahmatillah &

Ataulkarim, 2017) and adaptive NLMS filters (Biswas & Maniruzzaman, 2014; Maniruzzaman et al., 2012; Sharma, Mehra, & Singh, 2015). Also, in terms of magnitude squared coherence (MSC), amplitude spectrum, and power spectral density (PSD), graphically it is shown that the biorthogonal wavelet transform can remove the baseline wander more successfully at the desired level.

Materials and Methods

Real ECG record is acquired from the MIT-BIH database (Goldberger et al., 2000). The baseline wander noise signal is also used from the physionet noise stress test database (Goldberger et al., 2000). The ECG signal is then added with baseline wander for producing noisy ECG signal. To recover original ECG signal from the noisy signal three different denoising approaches have been utilized, such as biorthogonal wavelet transform, notch and adaptive NLMS filters. The block diagram of the adaptive filter, notch filter and discrete wavelet transform (DWT) is shown in Fig. 1, which represents the basic operation of each denoising approach.

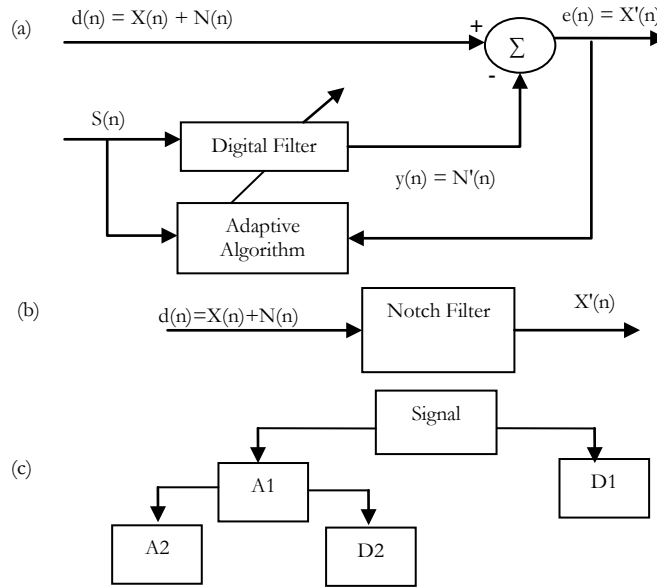


Fig. 1. Block diagram of (a) adaptive filter, (b) notch filter and (c) discrete wavelet transform decomposition process.

DWT is widely considered as an excellent method for signal processing. It decomposes the signal into varying resolution by applying a group of low and high pass filters. If $x(n)$ represents a discrete signal for n samples defined by $n = 0, 1, 2, \dots$, then the resulting coefficients of the wavelet series expansion are called the DWT of $x(n)$, which is written as,

$$W_{\phi}(j_0, k) = \frac{1}{\sqrt{M}} \sum_n x(n) \phi_{j_0, k}(n) \quad (1)$$

$$W_{\psi}(j, k) = \frac{1}{\sqrt{M}} \sum_n x(n) \psi_{j, k}(n) \quad (2)$$

Where $j \geq j_0$; $W_{\phi}(j_0, k)$ and $W_{\psi}(j, k)$ represents the approximation and details coefficients.

Now the Inverse Discrete Wavelet Transform (IDWT) for the discrete signal can be written as,

$$x(n) = \frac{1}{\sqrt{M}} \sum_k W_\phi(j_0, k) \phi_{j_0, k}(n) + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_k W_\psi(j, k) \psi_{j, k}(n) \quad (3)$$

Here, $j_0 = 0$, and $M = 2^j$ are considered to perform the summations over $j = 0, 1, \dots, J-1$ for each scale level and $k = 0, 1, 2, \dots, 2^j - 1$ for different translations in each scale levels. In Eq.(3) $x(n)$, $\phi_{j_0, k}(n)$ and $\psi_{j, k}(n)$ represents the functions for the n discrete variables.

The expansion function $\phi_{j_0, k}(n)$ is derived from a scaling function $\phi(n)$.

$$\phi_{j_0, k}(n) = 2^{j_0} / 2 \phi(2^{j_0} n - k) \quad (4)$$

The function $\psi_{j, k}(n)$ is derived from a wavelet function $\psi(n)$.

$$\psi_{j, k}(n) = 2^j / 2 \psi(2^j n - k) \quad (5)$$

The DWT is performed by decomposing a signal into elementary building blocks of varying resolution using a band of high and low pass filters h_ψ and h_ϕ respectively. The important step in DWT denoising process is the threshold selection. There are four different thresholding rules, rigsure, heursure, minimaxi, and sqtwolog thresholding, which are usually used during DWT signal decomposition (Misiti, Misiti, Oppenheim, & Poggi, 1996).

Performance parameter. Both time and frequency domain analyses are widely used as a popular method for performance evaluation. In this study, different performance parameters are analyzed in the time-frequency domain using Signal Processing Toolbox built-in MATLAB, which are given below.

SNRimp: The SNR is referred to as the ratio between the original signal and noise signal power. The SNRimp is written as

$$SNR_{imp} [dB] = SNR_{output} - SNR_{input} = 10 \log \left(\frac{\sum_n |x_n - x(n)|^2}{\sum_n |x_m - x(n)|^2} \right) \quad (6)$$

Where $x(n)$, x_n and x_m are the original, noisy and denoised ECG signal, respectively.

MSE: The MSE is defined as the average of squares of any given signal error, which represents difference among reconstructed ($x_m(n)$) and original form $x(n)$ of this signal.

$$MSE = \frac{1}{N} \sum_{n=0}^{N-1} [x(n) - x_m(n)]^2 \quad (7)$$

PRD: The PRD is expressed as the percentage of the ratio of the square root of difference square between the original $x(n)$ and recovered ($x_m(n)$) signal to the original $x(n)$ signal square.

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1} [x(n) - x_m(n)]^2}{\sum_{n=0}^{N-1} [x(n)]^2}} \times 100\% \quad (8)$$

MSC: MSC estimation is a frequency function of values from 0 to 1. It represents the degree of coherency between denoised (y) and original (x) signal at each frequency (Biswas & Maniruzzaman, 2015). More specifically, it is a function of PSD ($P_{xx}(f)$ and $P_{yy}(f)$) and cross PSD $P_{xy}(f)$ of x and y .

$$C_{xy} = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \quad (9)$$

PSD: PSD is the amount of power per unit bandwidth that represents the strength of power distribution of a signal at each frequency (Biswas & Maniruzzaman, 2015). It is usually estimated by taking the Fourier transform of the signal autocorrelation function. PSD of signal $x(n)$ is defined as

$$PSD = S_x(f) = \int_{-\infty}^{\infty} R_x(\tau) e^{-j\omega\tau} d\tau = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x(n)x(n+\tau) e^{-j\omega\tau} dnd\tau \quad (10)$$

Where $R_x(\tau)$ is autocorrelation function of $x(n)$. During PSD estimation, one-sided Fourier transform of the autocorrelation function is referred to as periodogram and two-sided Fourier transform is referred to as correlogram. Usually, the periodogram is less accurate compared to correlogram. In this study, PSD has been calculated by considering the hamming window with the sampling frequency of 200 Hz and a two-sided spectrum.

Results and Discussion

In this study, ten patients ECG records are imported from physionet MIT-BIH database (Goldberger et al., 2000) and added with the baseline wander noise of physionet noise stress test database. Noisy ECG is then analyzed using different wavelet families and thresholding rules up to twelve decomposition levels and SNRimp has been calculated at each decomposition level. Based on highest SNRimp, it is seen that wavelet 'bior1.1' and thresholding rule 'rigrsure' is suitable for baseline wander removal at level 11, which is shown in Table 1.

Table 1. SNRimp for selected wavelet, thresholding rule and decomposition level.

Noise	Highest SNR	Best Level	Thresholding Rule	Wavelet
Baseline				
Wander	3.557	11	rigrsure	bior1.1

After that, the selected wavelet (bior1.1), thresholding rule (rigrsure), and decomposition level (11) have been used to examine another 45 real ECG records. The performance of the selected denoising approach has been investigated by calculating different performance parameters. As the procedure is same for all 45 records, the performance of only 5 records has been shown in Table 2. From the tabular analysis, the small value of both MSE and PRD for all five ECG records has validated the effectiveness of biorthogonal wavelet-based denoising approach.

Table 2. Values of performance parameters for five records using thresholding rule 'rigrsure' and wavelet 'bior1.1'.

Record No.	MSE	NMSE	RMSE	NRMSE	PRD
101	11	3.5570	0.0304	0.2216	0.1742
103	11	2.9870	0.0356	0.2346	0.1887
105	11	5.1008	0.0280	0.1899	0.1672
106	10	3.9794	0.0390	0.2124	0.1974
107	11	0.9664	0.2415	0.2871	0.4914

A similar study of denoising baseline wander from 10 different ECG records has also been investigated using notch and adaptive NLMS filter. Finally, to confirm the superiority of the proposed approach, the performance of three denoising techniques have been compared in Table 3. From the table, it can be observed that for record number 109 the biorthogonal wavelet transform represents the highest SNRimp value of 8.0464 while the notch and adaptive NLMS filter has the lowest SNRimp value of -0.0046 and 1.6122 respectively. Similar results have been obtained for the other records as well. Therefore, the quantitative analysis among the three denoising techniques confirms that biorthogonal wavelet transform is three or more times superior compared to adaptive NLMS and notch filter for denoising baseline wander.

Table 3. SNRimp of notch filter, adaptive NLMS filter and biorthogonal wavelet transform.

Record No.	SNRimp in dB (For Baseline Wander)		
	Notch Filter	Adaptive NLMS Filter	Wavelet Transform
109	-0.0046	1.6122	8.0464
200	-0.0504	2.9178	6.1016
203	-0.0865	3.4707	5.2757
208	-0.0022	6.9684	7.1853
230	0.0045	1.2573	6.0251
219	0.0036	0.8451	5.9977

The qualitative analysis of the three denoising techniques performance in the time domain is represented in Fig. 2. The original, noisy and denoised ECG signal of the notch filter, adaptive NLMS filter and biorthogonal wavelet transform have been simulated by using MATLAB® 2012. In the figure, it is shown that denoised signal of biorthogonal wavelet transform is similar to main ECG signal. On the contrary, some irregularities of baseline wander noise are still present in the reconstructed signal of notch and adaptive NLMS filter. Moreover, during denoising, the important signal characteristics (i.e. duration and amplitude of some P-QRS-T waves) have been changed to some extent by notch and adaptive NLMS filter. Therefore, the time domain analysis clarifies that the biorthogonal wavelet transform reduces the baseline wander properly.

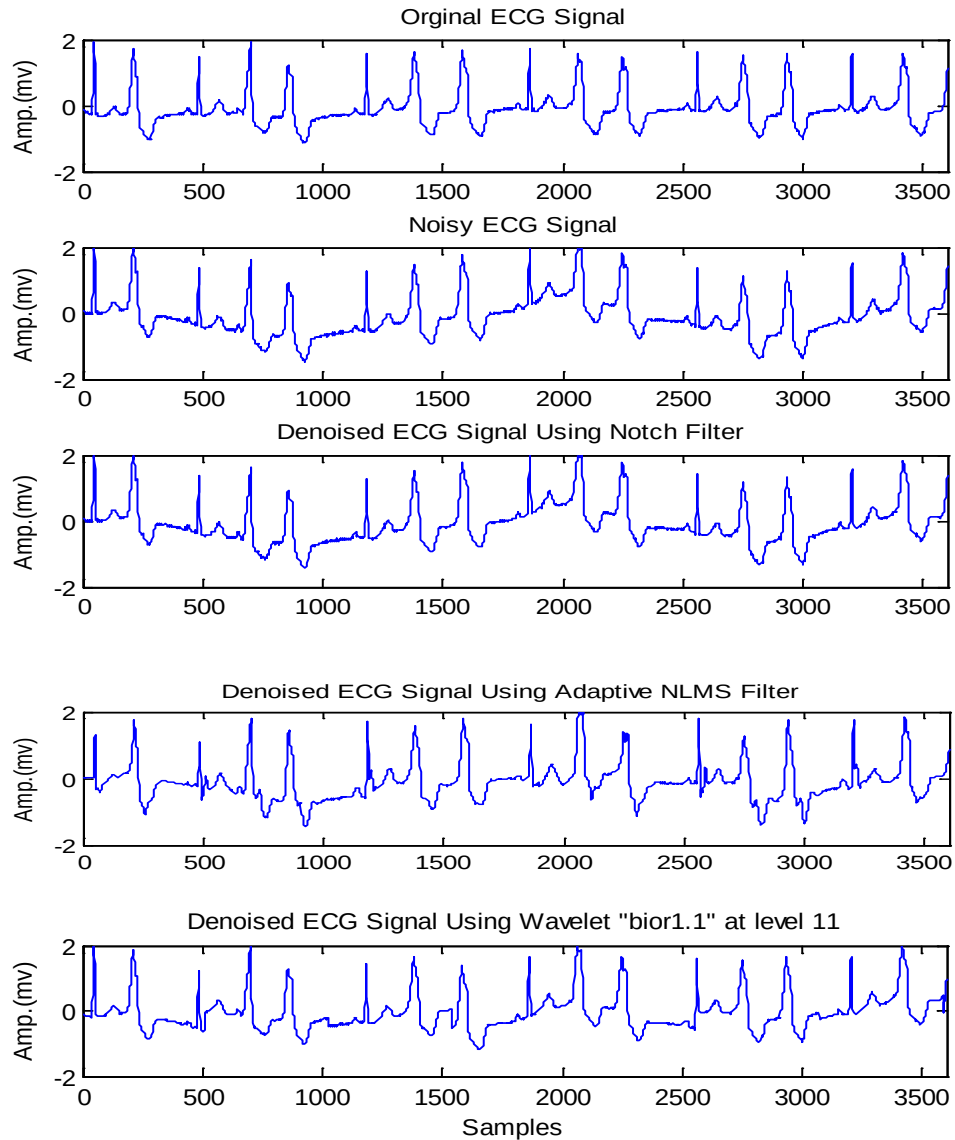


Fig. 2. Time domain analysis of original, noisy, notch filter, adaptive NLMS filter and wavelet transform denoised ECG signal (record no. 208).

The qualitative analysis of three denoising techniques performance is investigated again in the frequency domain in Fig. 3 based on the amplitude spectrum. It represents the variation of signal energy per unit frequency. From the figures, we can see that though the amplitude of the main ECG signal is low in the low-frequency region (below 1Hz), it has been increased in the noisy signal amplitude spectrum due to the addition of noise. Then the amplitude spectrum of the three denoising techniques shows that the signal amplitude has been reduced again in low-frequency region due to the removal of noise from the noisy signal, where the biorthogonal wavelet transform represents better performance compared to other techniques.

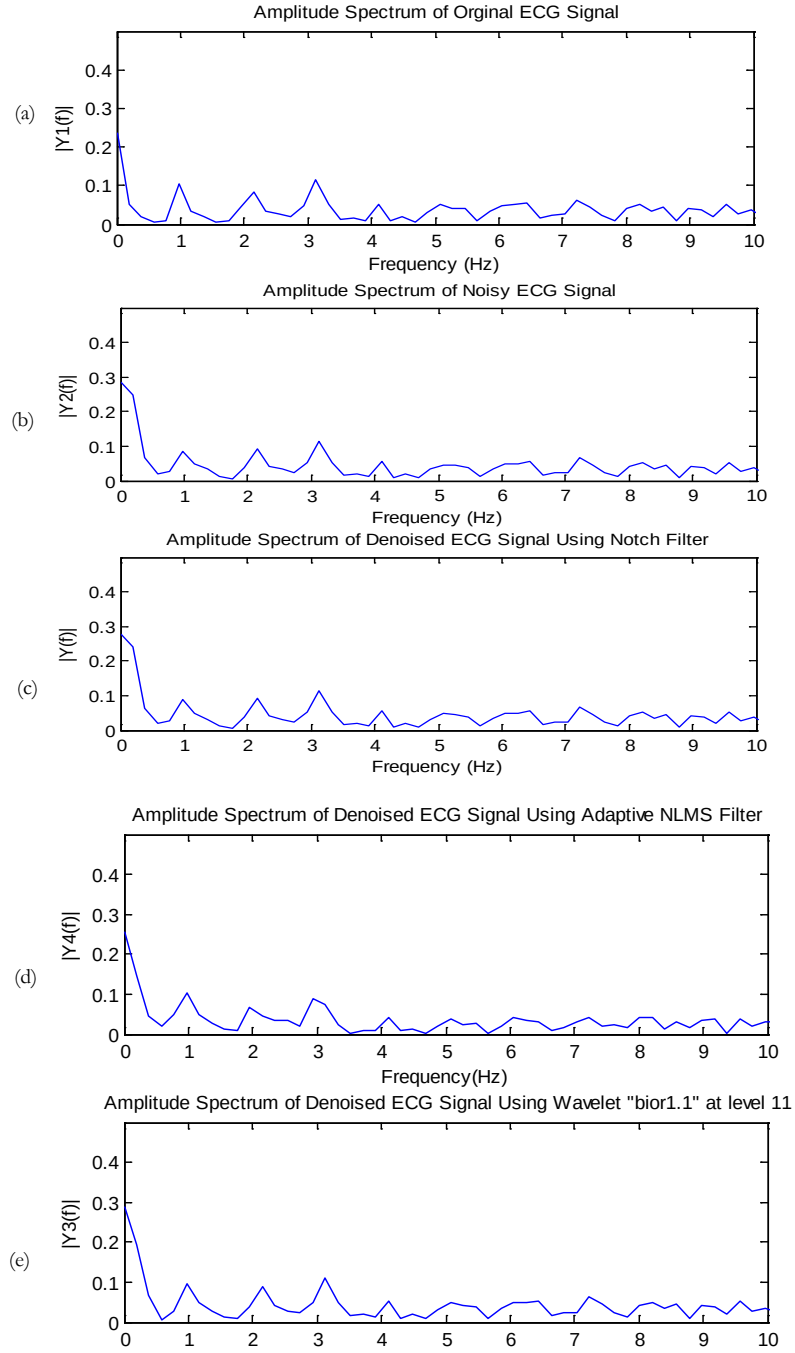


Fig. 3. Amplitude spectrum of (a) original, (b) noisy, (c) notch filter, (d) adaptive NLMS filter and (e) wavelet transform denoised ECG signal (record no. 108).

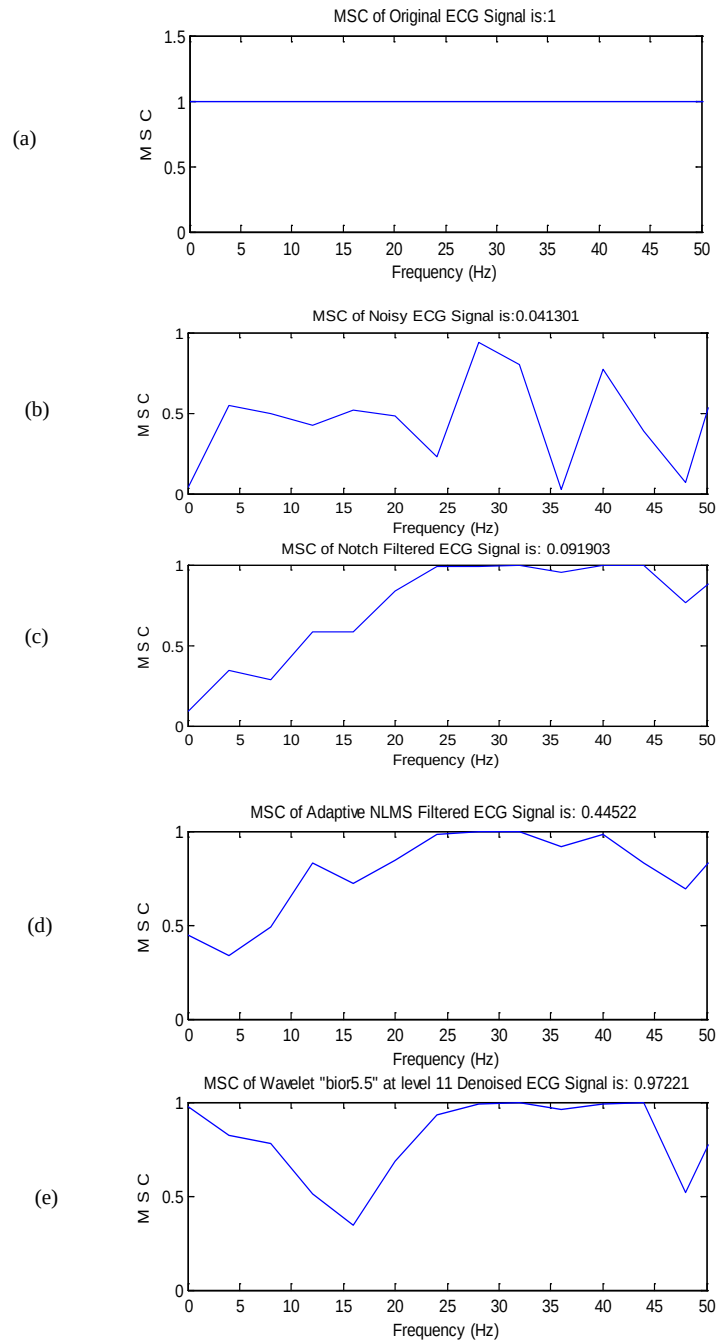


Fig. 4. MSC of (a) original, (b) noisy, (c) notch filter, (d) adaptive NLMS filter and (e) wavelet transform denoised ECG signal (record no. 108).

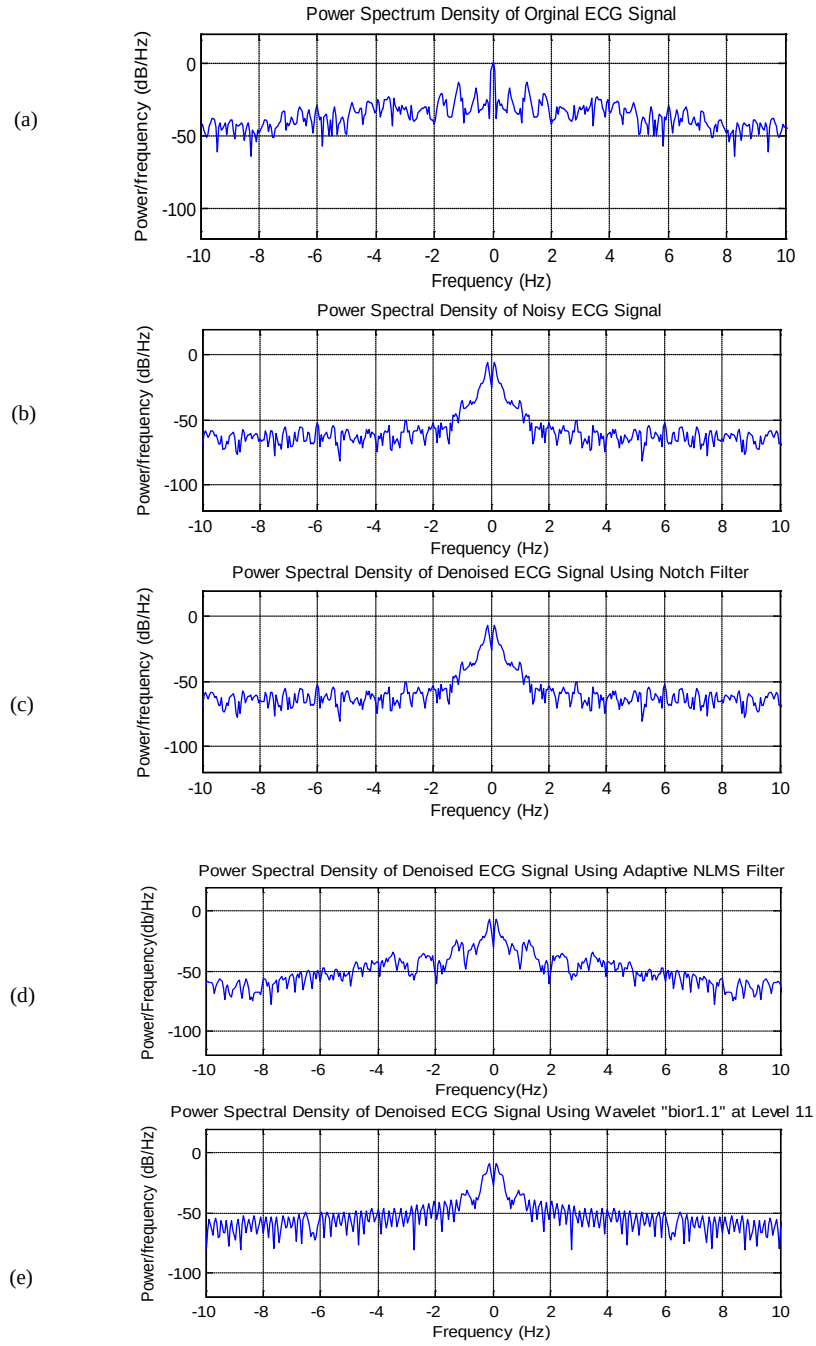


Fig. 5. PSD of (a) original, (b) noisy, (c) notch filter, (d) adaptive NLMS filter and (e) wavelet transform denoised ECG signal (record no. 210).

MSC, which is the frequency function of values from 0 to 1, has been utilized here and shown in Fig. 4 to analyze the degree of coherency between the denoised and original signal. Fig. 4 (a)-(e) represents the MSC estimation of the original, noisy, and three denoising techniques reconstructed ECG signals. From the figures, it can be seen that the coherency between noisy and original ECG signal is only 0.041301 in between 1 at 0.0978 Hz, where the degree of coherency has been increased to 0.091903, 0.44522 and 0.9772 respectively, for notch filter, adaptive NLMS filter and biorthogonal wavelet transform denoised signal. Therefore, the coherency of biorthogonal wavelet transformed signal is significantly higher than adaptive NLMS and notch filtered signal.

PSD, which is the power per unit bandwidth, has been used to analyze the power distribution of original, noisy and denoised signal at each frequency. It is an excellent tool to evaluate the denoising performance. Fig. 5 (a)-(e) represents the PSD estimation of original, noisy, and three denoising techniques reconstructed ECG signals. From the figures, it can be observed that noisy ECG PSD value is high (-6.049 dB/Hz) at 0.0978 Hz due to the distribution of noise power, which has been reduced to -6.669 dB/Hz, -6.788 dB/Hz and -9.317 dB/Hz respectively, for notch filter, adaptive NLMS filter and biorthogonal wavelet transform denoised signal. Therefore, the PSD estimation clearly represents the performance of these three techniques for denoising baseline wander where the biorthogonal wavelet transform shows a higher degree of accuracy.

As we know that the notch filter attenuates a narrow frequency range around noise frequency and removes some important frequency content of the ECG signal during denoising. Moreover, the adaptive filter has computational difficulty and stability issue for inaccurate step size. In that case, wavelet transform that has a higher degree of time-frequency resolution over the time-frequency plane becomes very effective in separating singularities and irregular structures from the ECG signal with little storage space.

In our study, we have found that, in denoising baseline wander, biorthogonal wavelet transform represents significant performance compared to notch and adaptive NLMS filters. Quantitatively, in Table 1, we can see that within five wavelet families (db, coif, sym, meyer, bior), biorthogonal (bior) wavelet shows better performance of SNR_{imp} because it is a combination of two orthogonal wavelet function one for decomposition and other for reconstruction. This combination generates different multiresolution analyses of ECG signal. Based on the performance of other parameters such as PRD, MSE, NMSE, RMSE, and NRMSE of Table 2, it is seen that the biorthogonal wavelet transform is good for denoising baseline wander. From Table 3, it has been shown that SNR_{imp} of the proposed biorthogonal wavelet transform is three or more times higher compared to notch and adaptive NLMS filter. Qualitatively, in Fig. 2, it is shown that the denoised signal of biorthogonal wavelet transform is highly similar to the original ECG signal, though the adaptive filtered and notch filtered signal contains some noise even after filtering. Fig. 3, Fig. 4 and Fig. 5 also demonstrated the significant outcome of biorthogonal wavelet transform based on other performance parameters such as amplitude spectrum, MSC, and PSD, respectively. Therefore, by these overall justifications, it can be said that biorthogonal wavelet transform is better compared to notch and adaptive NLMS filter for removing baseline wander from the ECG signal.

However, one study (Kaur, Singh, & Seema, 2011) for removing baseline wander, shows that the performance of IIR filtering method is better than the FIR filtering, Savitzky-Golay filtering, and Polynomial filtering, based on SNR, PRD and MSE. Another study on baseline wander removal from the ECG signal, demonstrated the superior performance of adaptive filter based on different parameters such as SNR, MSE and convergence rate (Qureshi et al., 2017). The significant performance of adaptive NLMS filter compared to LMS filter for removing different noises including baseline wander from ECG signal based on different performance parameters have been shown in our another study (Biswas et al., 2014). But in the current study, to select the best denoising

approach, we have done a detailed investigation of 5 wavelet families, and 4 thresholding rules up to 12 decomposition levels. Then the proposed approach has been validated by doing a broader analysis on 45 ECG signals and comparing its performance with notch and adaptive NLMS filters. The analysis result reveals the best performance of biorthogonal wavelet transform as low-frequency noise canceller compared to adaptive NLMS and notch filters. Therefore, a biorthogonal wavelet transform is more appropriate for denoising sensitive biomedical signals in all practical applications.

Conclusion

Time and frequency domain analyses of original, noisy and denoised ECG signals show that biorthogonal wavelet transform reduces baseline wander more noticeably. Compared to the notch and adaptive NLMS filter, the wavelet transform has the good performance of amplitude spectrum, MSC and PSD. Moreover, high SNR_{imp} and low PRD, and MSE values also clarify the supremacy of biorthogonal wavelet family. Therefore, for baseline wander ECG noise canceller, biorthogonal wavelet transform is the best technique than the other techniques.

This study mainly focuses on baseline wander removal from ECG signal by selecting a suitable wavelet family. Though wavelet transform represents the best outcome for eliminating low-frequency baseline wander noise, it has the limitation of removing the high-frequency noise and recovering the high-frequency content for low-frequency resolution at the high-frequency region of the signal. In that case, the wavelet packet transform that usually provides good frequency and time resolution by decomposing both lower and higher frequency components at each decomposition level may be more suited to remove the lower and higher frequency noises from the critical biomedical signals. Therefore, this study will be extended in future by investigating the performance of wavelet transform compared to wavelet packet transform for denoising both lower and higher frequency noises (baseline wander, 50 Hz power line interference, electrode movement and muscle artifacts etc.) from the ECG signal. Furthermore, it will be more interesting to make a broader study on such implementations for other biomedical signals, such as Electroencephalogram (EEG), and Electromyogram (EMG).

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