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Use of Transforms in Biomedical Signal Processing and Analysis

Ette Harikrishna and Komalla Ashoka Reddy

Abstract

Biomedical signals like electrocardiogram (ECG), photoplethysmographic (PPG) and blood pressure were very low frequency signals and need to be processed for further diagnosis and clinical monitoring. Transforms like Fourier transform (FT) and Wavelet transform (WT) were extensively used in literature for processing and analysis. In my research work, Fourier and wavelet transforms were utilized to reduce motion artifacts from PPG signals so as to produce correct blood oxygen saturation (SpO₂) values. In an important contribution we utilized FT for generation of reference signal for adaptive filter based motion artifact reduction eliminating additional sensor for acquisition of reference signal. Similarly we utilized the transforms for other biomedical signals.

Keywords: Fourier transform, biomedical signals, electrocardiogram signal, photoplethysmographic signal, wavelet transform

1. Introduction

The essence of mathematical design cannot be ignored in the analysis of real world engineering applications i.e. the research in engineering and mathematics is a two way parallel track that interrelates and coordinates towards value added research. In specific, the use of transforms in the field of electrical, electronic and communication engineering is unimaginable. In the present scenario of Covid-19 pandemic, world is looking to sustainable development of biomedical devices for critical monitoring and efficient vaccination for human survival [1–4]. In general, the Fourier transform (FT) is a mathematical tool which transforms the time domain signal into a frequency domain representation used in analysis of biomedical, wireless communication, signal and image processing applications. In literature, many researchers had used this tool in frequency domain analysis of all biomedical signals like electrocardiogram (ECG), photoplethysmographic (PPG) and blood pressure (BP).

In continuation to FT, different transforms were developed to analyze and design of various applications based on the requirement [5, 6]. In general, the FT is used in analysis of stationary signals; the wavelet transform (WT) is a mathematical tool used in analysis of both stationary and non-stationary signals. Discrete wavelet transform (DWT) used in enormous application in various engineering fields.

So, in this chapter we addressed some of the research challenges in ECG and PPG signal processing using Fourier and Wavelet transforms.

2. Transforms and its use in biomedical signal analysis

2.1 Transforms

Jean-Baptiste Joseph Fourier a French mathematician had developed theoretical and mathematical framework for Fourier analysis and harmonic analysis, which was laid down foundation to other transforms and important applications. Forward and inverse transform of a continuous time Fourier transform (CTFT) for a time domain signal $x(t)$ is defined as

$$X(j\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \quad (1)$$

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(j\omega) e^{j\omega t} d\omega \quad (2)$$

Here, $e^{-j\omega t}$ is called as a basis function for CTFT.

For ease of processing the continuous time signal is converted into discrete time, then the corresponding forward and inverse transform of a discrete Fourier transform (DFT) for a discrete time signal $x(n)$ is defined as

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi nk}{N}}; \text{ for } k = 1, 2, 3, \dots, N \quad (3)$$

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j\frac{2\pi nk}{N}}; \text{ for } n = 1, 2, 3, \dots, N \quad (4)$$

Here, $e^{-j\frac{2\pi nk}{N}}$ is called as a basis function for DFT.

Similarly, the continuous wavelet transform (CWT) is defined as

$$F(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-a}{b}\right) f(t) dt \quad (5)$$

where, $f(t)$ is a time domain signal, $\psi(t)$ is a basis function also called as mother wavelet; $F(a, b)$ is WT of a signal $f(t)$; 'a' and 'b' are shifting and scaling parameters respectively;

Discrete WT (DWT) uses a series of low pass filters (LPF) and high pass filters (HPF) to decompose the signal of interest into different scales as approximate (A_j) and detailed coefficients (D_j). The output coefficients of the LPF are called approximations while the output coefficients of the HPF are called details.

A 3-stage DWT decomposition tree is illustrated in **Figure 1**.

After first level of decomposition A_1 and D_1 will be the outputs, D_1 will be stored in **C** matrix as shown in **Figure 1**. A_1 will be further decomposed in 2nd level of decomposition as D_2 , A_2 . D_2 will be stored in **C** matrix, and A_2 will be decomposed in 3rd level of decomposition as D_3 , A_3 . Then A_3 and D_3 will be stored in **C** matrix, i.e. **C** matrix consists of concatenated A_3 , D_3 , D_2 , D_1 coefficients. **L** matrix stores the length of each corresponding approximate and detailed coefficient as in **C** matrix.

C matrix gives the concatenated approximate and detail coefficients. **L** matrix gives length of each coefficient. **C** and **L** matrices along with suitable filters will be used to get back the original time domain signal $f(t)$.

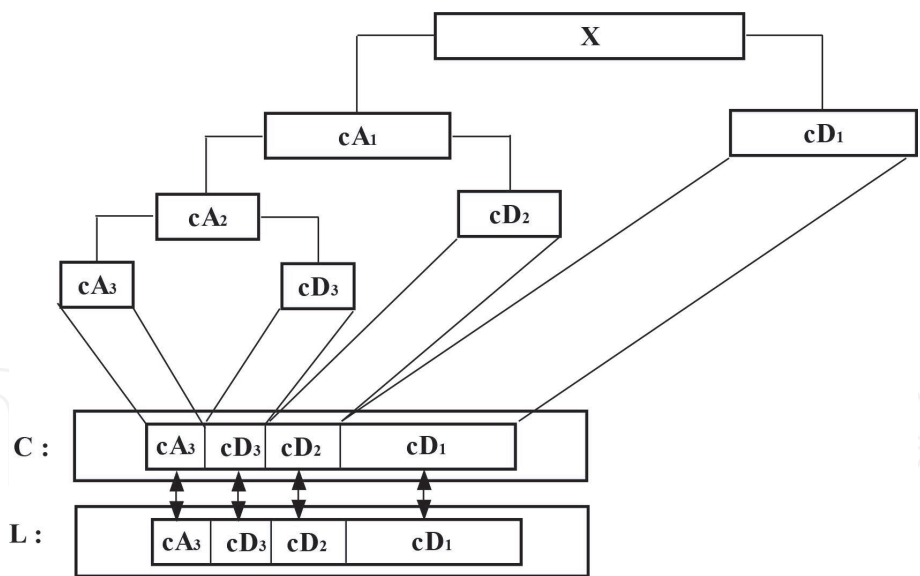


Figure 1.
A sample of 3-stage Wavelet decomposition tree, In Matlab® ‘wavedec’ command will decompose signal of interest and gives **C** and **L** matrices.

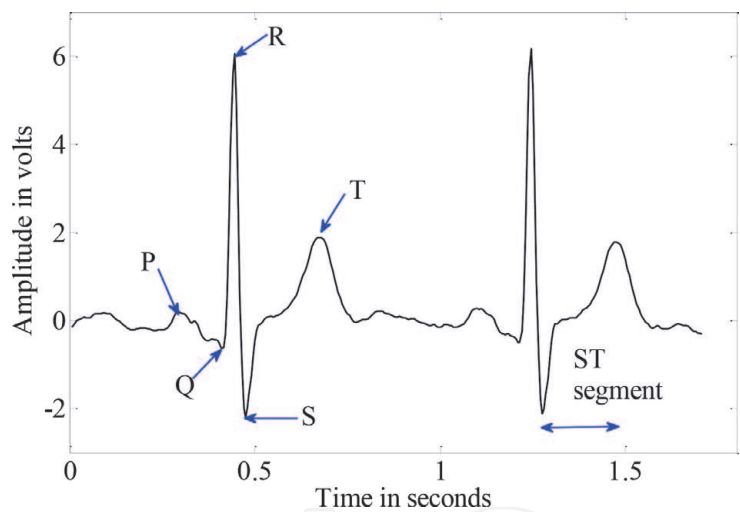


Figure 2.
Typical recorded ECG signal in the laboratory.

2.2 Biomedical signals

The Electrocardiogram (ECG) is an electrical manifestation of contractile activity of the heart, is a representation of instantaneous electrical activity of the heart during its contraction and relaxation over a period of time. A standard 12 leads ECG is recorded with the help of surface electrodes placed on the limbs and chest. In general, ECG is a widely accepted diagnosis tool in clinical validations of heart related diseases. **Figure 2** shows a typical ECG signal, marked with all the characteristic waves and durations such as P wave, QRS complex wave, T wave and ST segment [7].

Monitoring of blood oxygen saturation (SpO_2) is one of the important parameter to know the health status of Covid-19 affected patient. Pulse oximeter uses sensor probes to record photoplethysmographic (PPG) signals so as to estimate the SpO_2 values. Typical recorded PPG signal is shown in **Figure 3**.

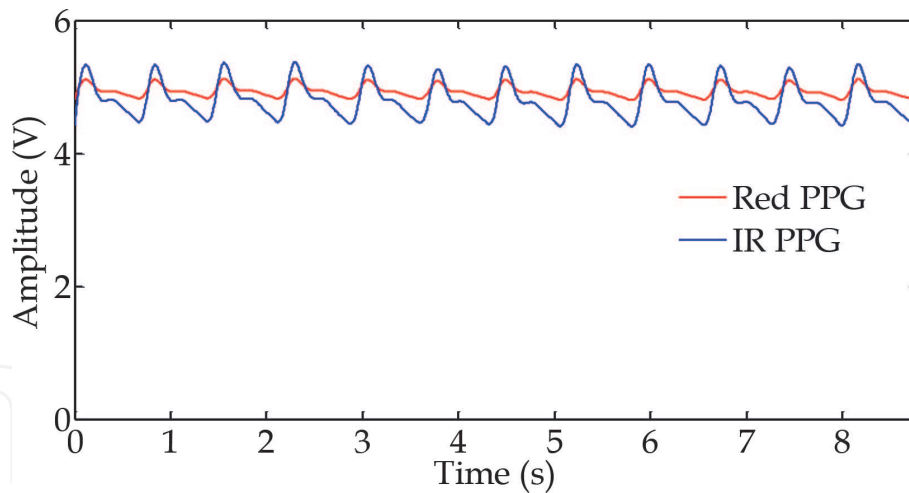


Figure 3.
Typical recorded PPG signal in the laboratory.

2.3 Biomedical signal processing using transforms

Fourier transform (FT) is used to analyze the behavior of biomedical signals in frequency domain. In Matlab FFT command can be used to get the frequency domain signal.

Following is the sample code to plot time and frequency domain signals.

```
load ecg_signal.txt;
ecg_signal_fft=fft(ecg_signal);
figure(1)
subplot(211)
plot(ecg_signal)
subplot(212)
plot(ecg_signal_fft)
```

Some additional modifications will be done in the program to get the following plots.

In the bottom trace of **Figure 4**, it can be seen that the frequency domain components of ECG signal are extending from 0 to 100 Hz, the main source of noise 60 Hz power line interference (PLI) the spike at 60 Hz can be observed. So, the complete frequency domain behavior of signal can be computed using fft command.

Similarly, the frequency domain components of PPG signal is shown in **Figure 5**. It can be seen from the bottom trace that frequency components present in PPG signal are pulse rate or heart rate component and MA noise component. Likewise it can be continued for many biomedical signals to see the frequency domain behavior of the signal.

So, use of Fourier transform in de-noising of signal can be described as shown in **Figure 6**.

In general adaptive filter provide a viable solution when signal and noise are in same frequency range. Adaptive filter requires a two input signals [8].

For example, in a power line interference cancelation from ECG signal, one is recorded noisy ECG signal and other is power line noise. So, here a synthetic noise reference signal will be generated using Fourier transform which will be used as another input to the adaptive filter will potentially eliminate additional sensor for acquisition shown in **Figure 7**.

A synthetic noise reference signal is generated for use in adaptive filtering without using any extra hardware. It is generated from the motion corrupted signal

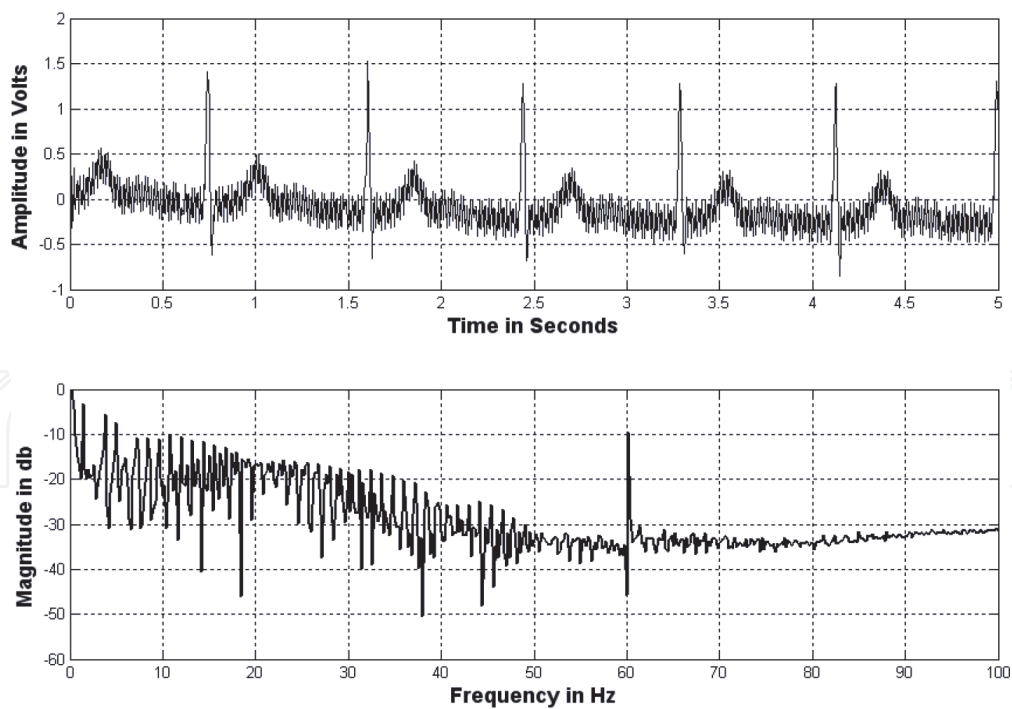


Figure 4.
Recorded ECG signal in top trace and its corresponding spectrum after application of FFT in bottom trace.

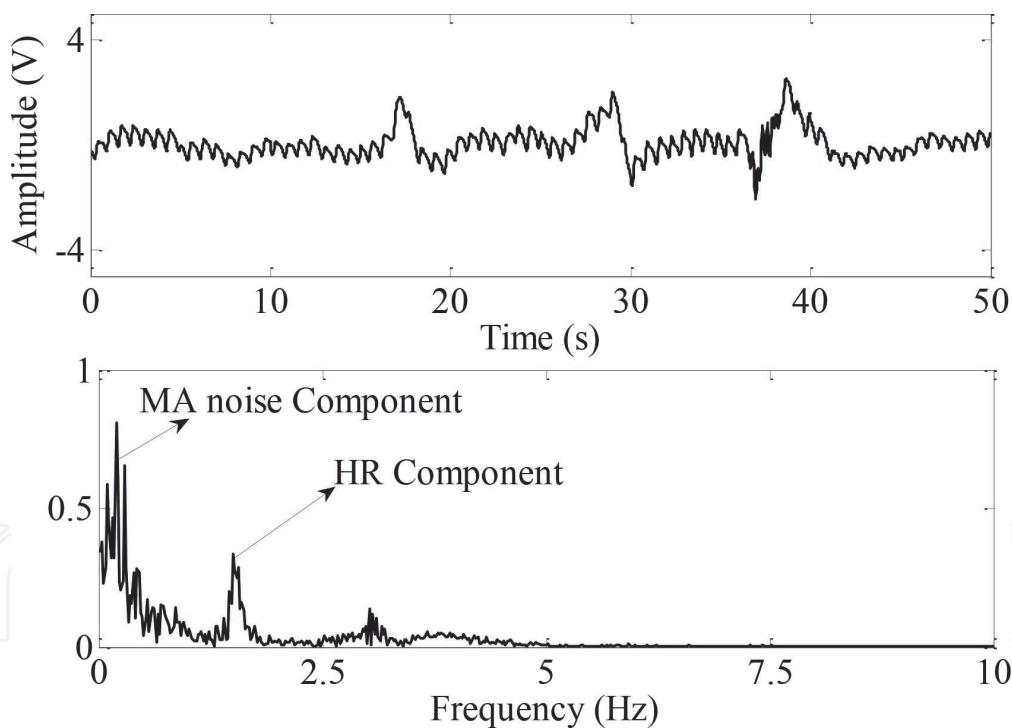


Figure 5.
Recorded PPG signal in top trace and its corresponding spectrum after application of FFT in bottom trace.

in the following way. The frequency spectrum of MA corrupted PPG signal consists of various frequency components, the pulsatile (0.5–4 Hz), respiratory activity (0.2–0.35 Hz) and MA noise component (0.1 Hz or more) information. By setting the co-efficients of cardiac and respiratory activity frequency components in the spectrum of MA corrupted PPG to zero, a modified spectrum corresponding to noise is obtained. By applying inverse Fourier transform to this modified spectrum, a synthetic noise reference signal is generated. The corresponding adaptive filter is shown in **Figure 8**.

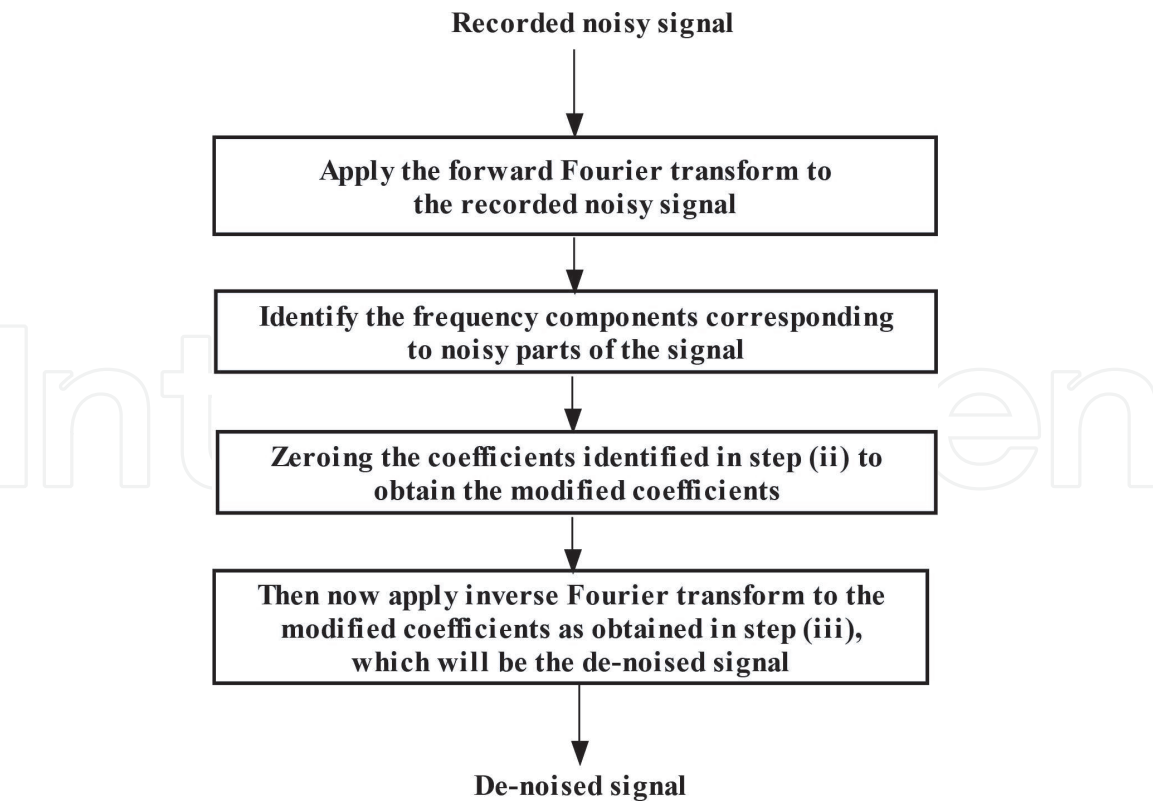


Figure 6.
Flowchart for de-noising of recorded signal using Fourier transform.

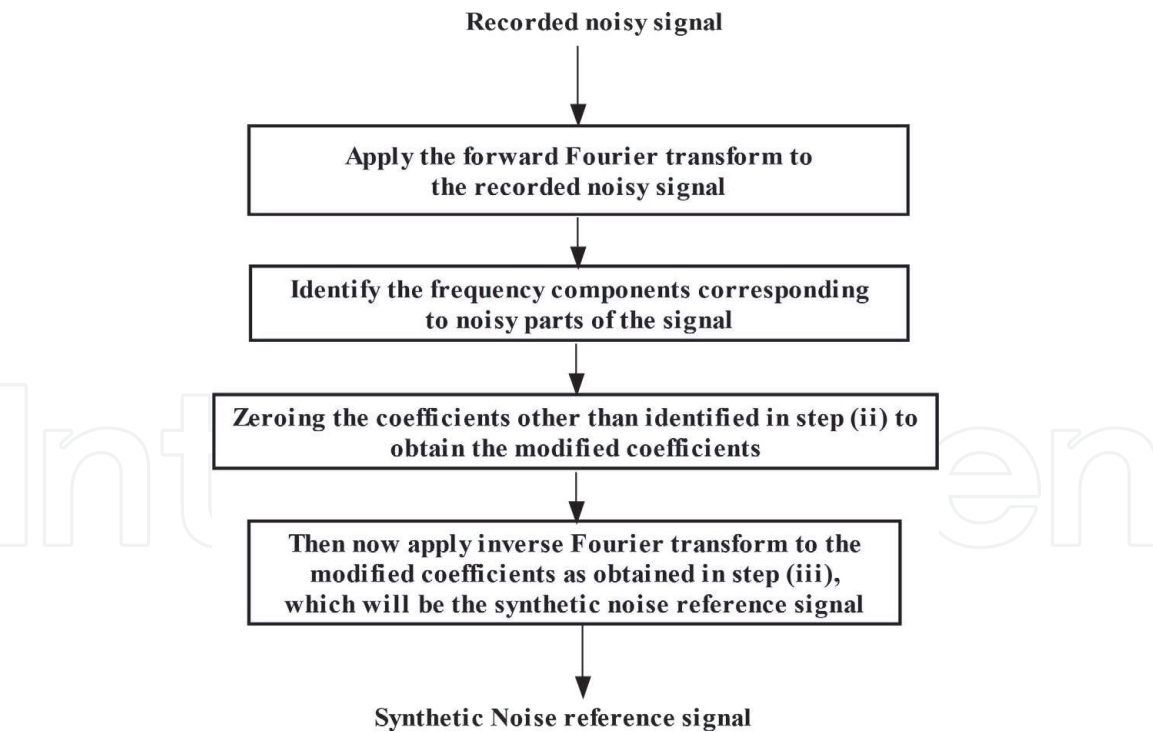


Figure 7.
Flowchart for generation of synthetic noise reference signal using Fourier transform.

With the help of LMS adaptive algorithm, MA noise is removed by estimating the synthetic noise reference signal and adapting the filter coefficients based on filter order. The necessary equations to implement the proposed method are given below:

$$\hat{S}(n) = S(n) + N(n) - \hat{N}(n) \tag{6}$$

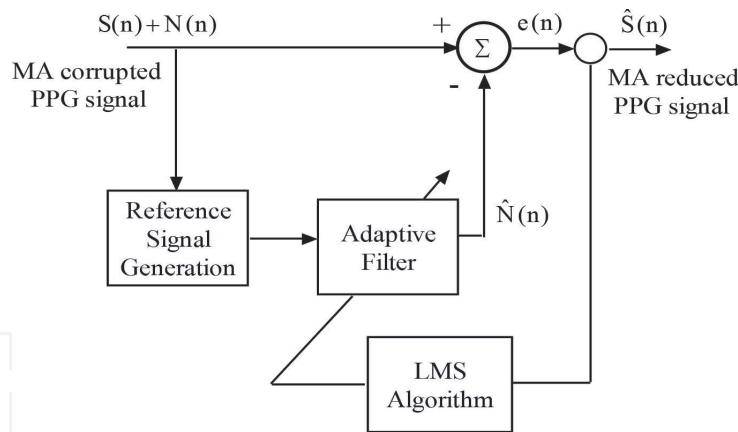


Figure 8.
Motion artifact reduction from PPG signals using Adaptive filter.

$$\hat{N}(n) = \sum_{i=0}^L w_i N_R(n - i) \tag{7}$$

$$w_i(n + 1) = w_i(n) + 2\mu S(n) N_R(n - i) \tag{8}$$

where $i: 0,1,2, \dots, L$, L : filter order, $S(n) + N(n)$: MA corrupted PPG signal, $\hat{S}(n) = e(n)$: MA reduced PPG signal, $\hat{N}(n)$: estimated synthetic noise reference signal, and $N_R(n)$: the synthetic noise reference signal.

The result of above methodology is presented in **Figure 9**, below. **Figure 9(b1)** represents the generated synthetic noise reference signal which potentially eliminates the additional sensor for data acquisition.

The biomedical signals such as ECG and PPG signals are quasi periodic signals i.e. the period of the signal continuously changes with time, but it is a periodic signal. In general, the pure periodic signals are stationary in nature means its period will be constant irrespective of time. So, Fourier transform is not sufficient to analyze the quasi-periodic signals. Wavelet transform will provide a viable solution to the same [9, 10].

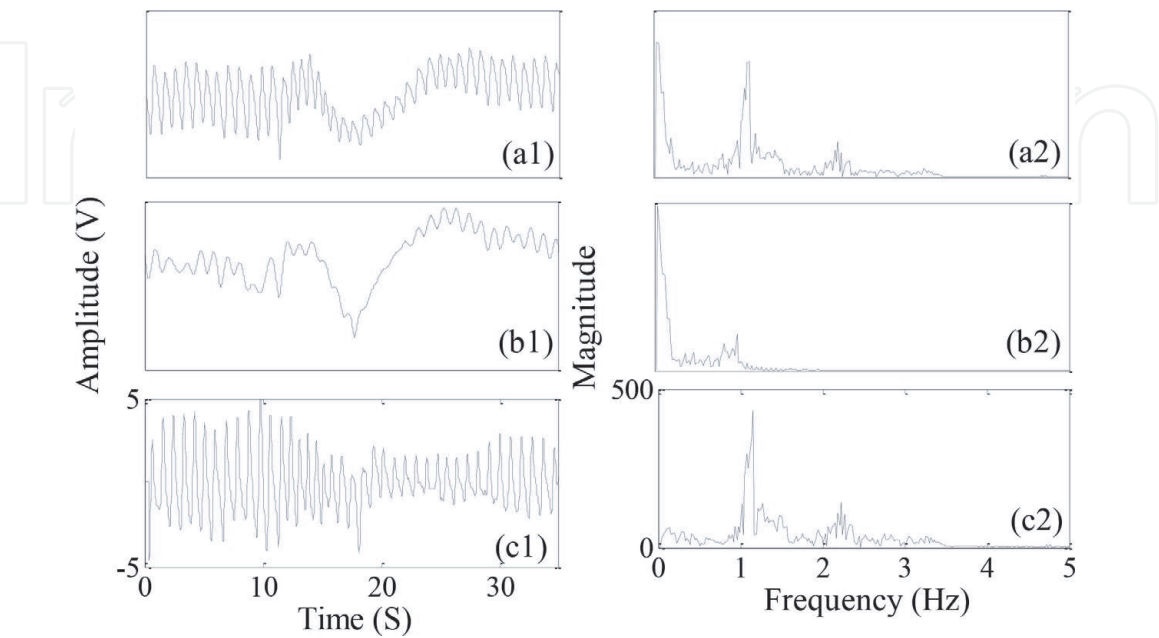


Figure 9.
Recorded PPG signal in (a1), generated MA synthetic reference signal in (b1) and MA reduced PPG signal in (c1) and their corresponding spectra in (a2)-(c2) respectively.

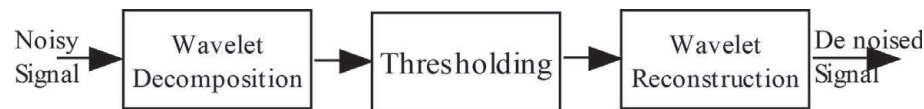


Figure 10.
Wavelet Denoising methodology.

The general de-noising procedure follows the steps described below and shown in **Figure 10**.

Decomposition: Choose a wavelet and choose a convenient level N for decomposition. Compute the wavelet decomposition of the signal s at level N .

Thresholding detail coefficients: For each level from 1 to N , select a threshold and apply soft or hard thresholding to the detail coefficients.

Reconstruction: Perform the wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N .

There are two important steps: how to choose the threshold, and how to perform the thresholding [10]. In hard thresholding process, the elements whose absolute values are lower than the threshold will be set to zero. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, remaining coefficients are compressed.

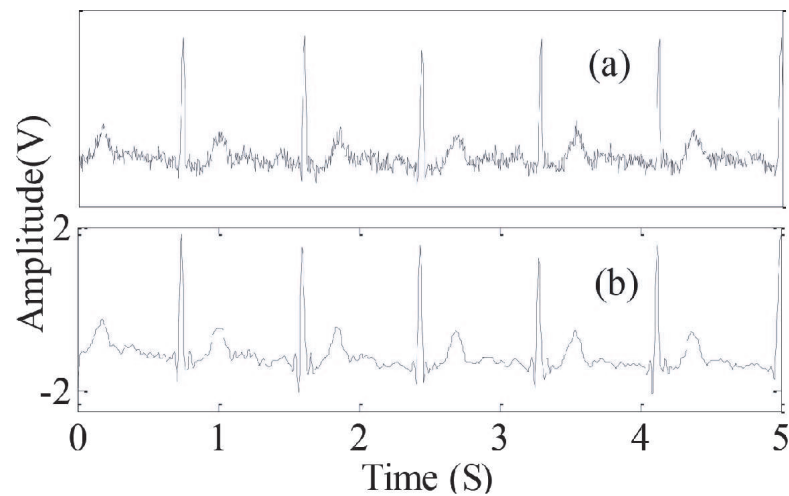


Figure 11.
(a) ECG signal corrupted with Electromyography signal (b) De-noised ECG signal using wavelet de-noising methodology.

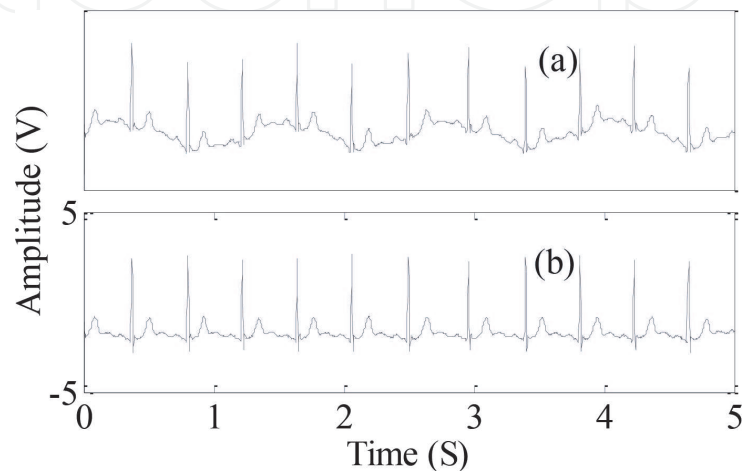


Figure 12.
(a) ECG signal corrupted with baseline noise (b) De-noised ECG signal using wavelet de-noising methodology.

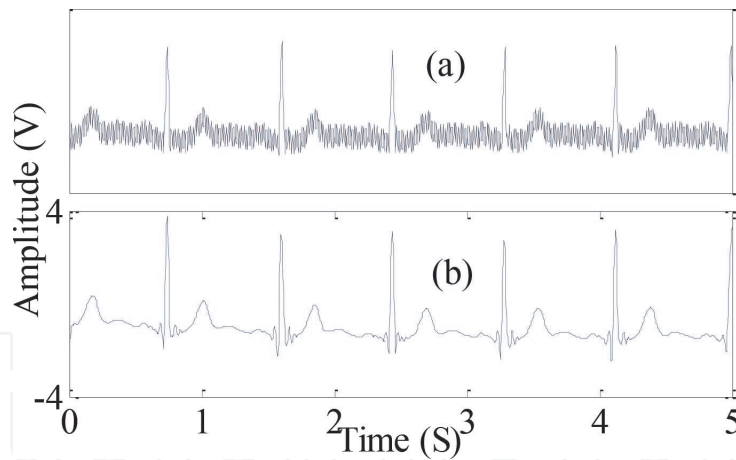


Figure 13.
(a) ECG signal corrupted with power line noise (b) De-noised ECG signal using wavelet de-noising methodology.

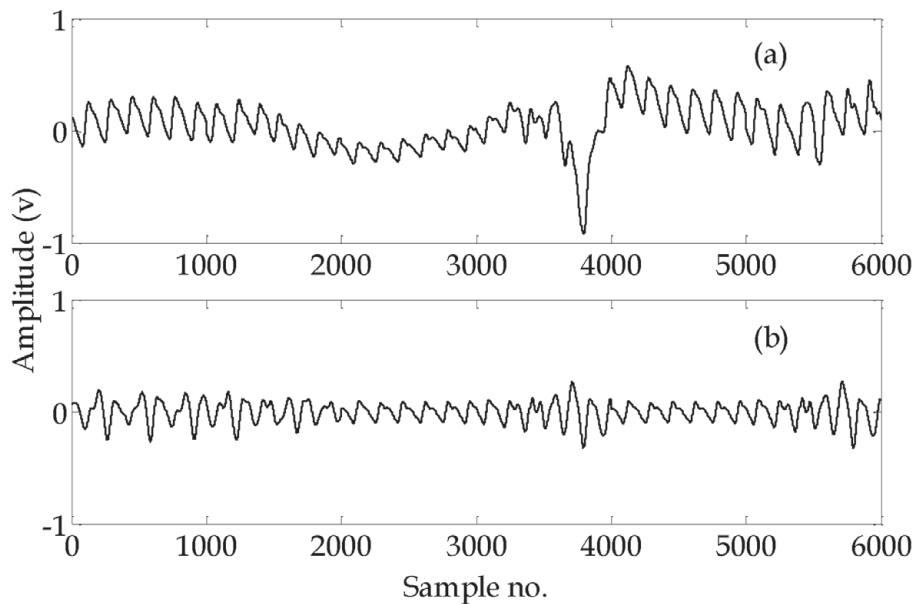


Figure 14.
(a) PPG signal corrupted with MA noise (b) De-noised PPG signal using wavelet de-noising methodology.

The same results were presented in **Figures 11–13**. Similar results were presented for PPG signal as shown in **Figure 14**.

3. Conclusions

Transforms like Fourier and wavelet transforms were used in biomedical signal analysis and processing. Fourier and wavelet transforms were utilized to reduce motion artifacts from PPG signals so as to produce correct blood oxygen saturation (SpO₂) values. In an important contribution we utilized FT for generation of reference signal for adaptive filter based motion artifact reduction eliminating additional sensor for acquisition of reference signal.

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