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Adaptive Symlet Filter Based on ECG Baseline Wander Removal

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Abstract: In this paper, proposed a new approach of combining the hybrid soft computing technique called Adaptive Symlet Wavelet Transform (ASWT) filter. The baseline wanders (BW) noise removal from an ECG signals to minimize distortion of the S-T segment of the ECG signal specially that have high sampling frequencies. Therefore, when using Symlet Wavelet Transform (SWT) to analysis the ECG signal can cause problems to analysis, exclusively when examining the content of the ECG signal at low-frequency such as S-T segment. The corresponding frequency components of the approximation coefficients at level number seven are (0–3.9) Hz. Since the BW frequency is below 0.5 Hz and ST segment frequency between (0.67–4) Hz. The adaptive filter with a unity reference signal used to remove the BW noise below 0.5 Hz from the lowest level of the approximation coefficient of the decomposed ECG signal. The denoising output from adaptive filter and the output from SWT (the other detail coefficients) will use as an input to ISWT for reconstruction ECG signals with the remove BW signal. This method represents a very effective filter for BW noise removal, as it does not need for any computation process of reference point.

Keywords: S-T segment; Symlet transform; ECG noise removal, Baseline Wander.

1 Introduction

The major causes of death in the world are mostly due to heart diseases. Therefore, it is necessary to have suitable methods for early detection of heart condition of the patient. The main tool that is widely used to understand the cardiac condition is an electrocardiogram (ECG) [1]. The S-T segment signifies the part of the ECG signal between T wave and the QRS complex. Changes in the ST segment that suggest heart muscle ischemia caused by inadequate blood supply. Together with T-wave shifts, the depression and analysis of the ST segment suggest that the ischemia area is around the applied lead. Therefore, ST segment analysis is an important task in cardiac diagnosis [2]. ECG signal is usually infected with various kinds of noise, namely Baseline Wander (BW) noise, Motion Artefacts (EA) noise, Muscle Artefacts (MA) noise, and Power

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Line Interference (PLI) noise [3, 4]. The baseline wandering drift, noise is occurring largely accompanied by ECG signals at low frequency oscillation on the ECG due to the poor electrode contact, body movement and respiration. It contains frequency below 1 Hz (or more common and more accurate below 0.5Hz) [5]. BW makes it difficult for ECG records to be analysed automatically and manually, particularly the measurement of ST segment deviation used for diagnostic ischemia. From the time when the baseline wandering spectrum and the low frequency portion of the ECG signal usually overlap, removing the baseline wandering may lead to distortion of the key medical data, mainly distortion of the ST section, this occurred especially at ECGs that have high frequency sampling [6].

2 Related Work

The ECG signals tend to be non-stationary signals. Therefore, the useful and powerful techniques that use to analyse such this type of signals is the family of the wavelet filter [7]. From Fig. 1 the power spectral analysis of ECG components P, T and QRS complex waves and noise, which is showing that noise and ECG components have different frequency content [8].

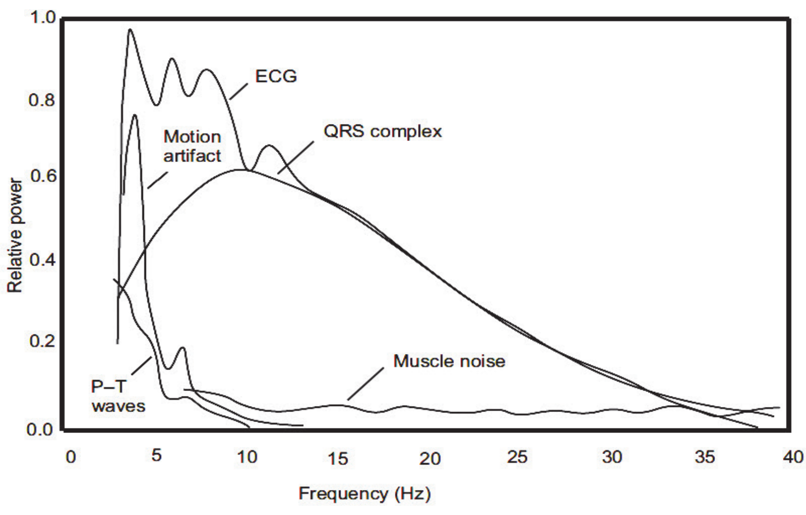

Fig. 1 – *Relative power spectra of the contaminated ECG Signal.*

Thus the general denoising procedure principles and the basic version of the procedure as shown in Fig. 2 and the denoising steps as the follows:

- ❖ *Signal decomposition.*
  - Select WT and the decomposition level *N*.
  - Calculate the WT decomposition of the signal *S* at *N* level.

- *Detailed threshold coefficients.*
  - Choose a threshold and use soft thresholding method for all levels from level 1 to level *N*.
- *Signal reconstruction.*
  - Calculate the restored WT using the initial N-level raw calculation coefficients, then all the adjusted 1 to N-level component coefficients.

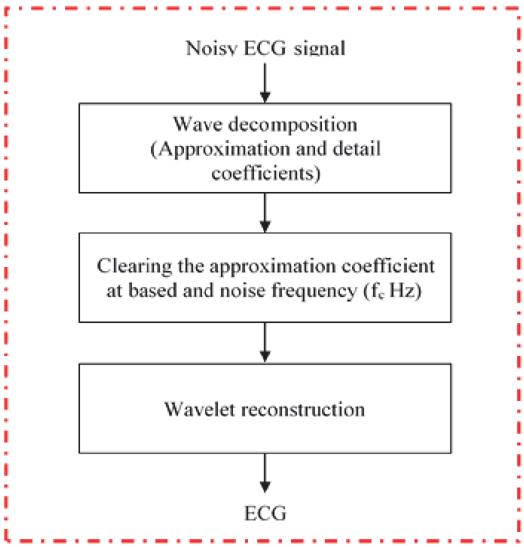

Fig. 2 – *General block diagram for de-noising using DWT sub-band analysis and synthesis.*

Generally, the SWT is also referred to as a decomposition by WT filter banks. This is because the DWT uses two filters to degrade the signal into different scales, a high pass filter (HPF) and a low pass filter (LPF). The output coefficients of the HPF are called information while approximations are called the output coefficients of the LPF. The wavelet decomposition tree is an iteration process of successive approximations, which in effect decomposes one signal into the many components of lower resolution. The equivalent LPF with the de-noising signal frequency response should not affect the spectrum of the ECG signal's beneficial portion. The cutoff rate must therefore be lower than $1/T$. As a result, the K^{th} decomposition rate's time resolution to must be higher or lower than T. The time resolution of the K^{th} decomposition level equals $2k/f_s$. Therefore, the price of K must be chosen to satisfy the condition in (1) [9]:

$$\frac{2^k}{f_s} \geq 1, \tag{1}$$

where f_s is sampling frequency and k is the number of sub-band (levels). **Table 1** shows the bandwidth of the DWT sub-bands of different sampling frequencies and they calculated based on (1).

Table 1
DWT sub-bands Bandwidth for different sampling frequencies.

DWT Levels	Sampling frequency (Hz)				
	128	**250**	**360**	**500**	**1000**
cD1	64 – 128	125 – 250	180 – 360	250 – 500	500 – 1000
cD2	32 – 64	62.5 – 125	90 – 180	125 – 250	250 – 500
cD3	16 – 32	31.25 – 62.5	45 – 90	62.5 – 125	125 – 250
cD4	8 – 19	15.62 – 31.25	22.5 – 45	31.25 – 62.5	62.5 – 125
cD5	4 – 8	7.81 – 15.62	11.25 – 22.5	15.6 – 31.25	31.25 – 62.5
cD6	2 – 4	3.9 – 7.81	5.62 – 11.25	7.81 – 15.62	15.62 – 31.25
cD7	1 – 2	1.95 – 3.9	2.81 – 5.62	3.9 – 7.81	7.81 – 15.62
cD8	0.5 – 1	0.97 – 1.95	1.4 – 2.81	1.95 – 3.9	3.9 – 7.81
cA8	0 – 0.5	0 – 0.97	0 – 1.4	0 – 1.95	0 – 3.9

3 The Proposed Method

In the proposed method, the ECG signal with BW noise are decomposed up to seven levels using SWT. The frequency components of the approximation coefficients at level seven are (0 – 3.9) Hz. Then subjected the approximation coefficient A_7 to the adaptive filter with unity reference input for the prevention of distortion of the ST segment as displayed in Fig. 3. The output from adaptive filter and the output from SWT, detail coefficients, will use as an input to ISWT for reconstruction ECG signals with removing BW signal. This method represents a very effective filter for BW noise removal, as it does not need for any computation process of reference point and when uses DWT for the analysis of the inherently ECG signals can cause problems to analysis, exclusively when investigative the low-frequency ST segment.

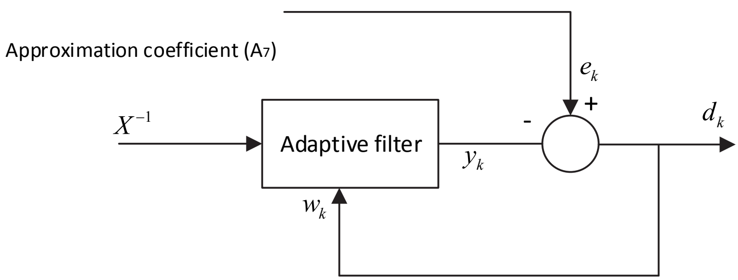

Fig. 3 −*Adaptive Filtering for BW noise Removal.*

The transfer function adaptive filter from the primary input to the noise canceller output is now resulting. The appearance of the output of the adaptive filter y_k is assumed by:

$$y_k = w_k \cdot 1 = w_k \,. \tag{2}$$

The w, bias weight is updated as said by the LMS update next equation:

$$w_{k+1} = w_k + 2\mu(\mathrm{e}_k \cdot 1)\,, \tag{3}$$

$$y_{k+1} = y_k + 2\mu(d_k - y_k) = 2\mu d_k + (1-2\mu)y_k \,. \tag{4}$$

Then, by use take the z-transform of both the sides yields the steady-state result:

$$Y(z) = \frac{-2\mu}{(1-2\mu)-z} D(z)\,. \tag{5}$$

Also, the error signal of the Z-transform is:

$$E(z) = D(z) - Y(z) = \frac{z-1}{z-(1-2\mu)} D(z)\,. \tag{6}$$

Finally, final transfer function as:

$$H(z) = \frac{E(z)}{D(z)} = \frac{z-1}{z-(1-2\mu)}\,. \tag{7}$$

Therefore, we obtain that the bias weight filter is a high pass filter using a zero frequency of the unit circuit in a zero and a pole on the real axis by the side of a distance of 2μ to the left of zero. The smaller μ, the higher the electrode's location and the nearest zero, the degree is exactly zero, i.e. the DC rate is only eliminated.

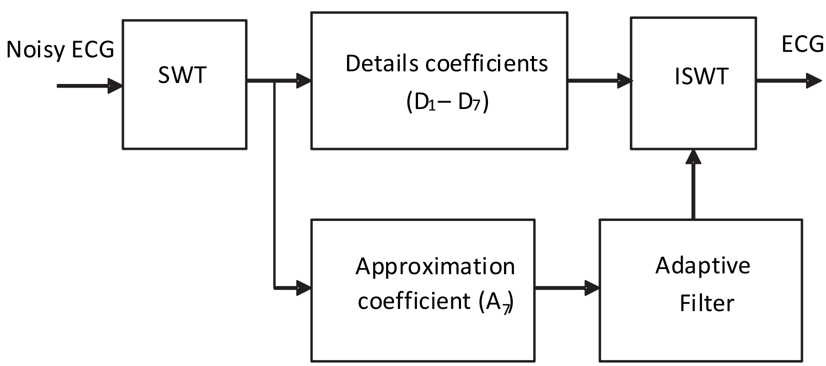

Fig. 4 – *Block diagram of the proposed adaptive ASWT for BW noise removal.*

The single weight, noise generator, which acts as a high-pass filter, can not only eliminate static bias but also gradually modify the primary input. In the case of any problem, the deviation of the level of bias and even if the drift is slow enough, the weight of the bias adapts alternately to track and remove the drift. By a biased weight together with normal weights when the noise is cancelled to fit, bias or drift removal can be achieved at the same time through random interference or the elimination of periodic [10, 11].

The proposed filter method, as the block diagram, as shown in Fig. 4. For adaptive filtering of BW signal, only one sub-band (weight) required, and the reference input is a constant with a value of one.

4 Results and Discussion

Fig. 5 illustrations the original ECG signal have 1 kHz sampling frequency with liner BW noise before de-noising. Which is described the original ECG signal by adding a linear BW noise signal before passing through Sym8-WT.

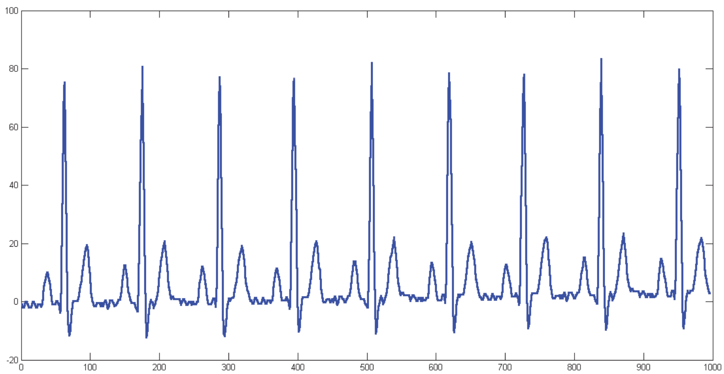

Fig. 5 − *Original ECG signal at 1 kHz sampling frequency with liner BW noise.*

Firstly; the ECG signal decomposed using Sym8 at level 7 to remove the BW noise without using adaptive filter and the results as shown in Fig. 6. Since the bandwidth for sub-band at level 7 equal to (0 − 3.9) Hz for sampling frequency 1 kHz. Therefore, when remove the noise from ECG signal that lead to remove some of low frequency content from the ECG signal, especially at ST- segment as shown in Fig. 7.

Figs. 5, 6 and 7 illustrate the ECG diagram where the frequency is appropriate with possible test noise compared to no noise. The ECG signal is decomposed using Sym8 at level 7 to remove BW noise without using the conditioning filter. Therefore, when removing noise from the ECG signal that leads to the removal of any low frequency content of the ECG signal, especially in ST, it is also clear that abnormal ST segments are reviewed based on the reasons described in the ECG revisions and standards as in the case of ventricular hypertrophy, Pericarditis and Brugada syndrome [12].

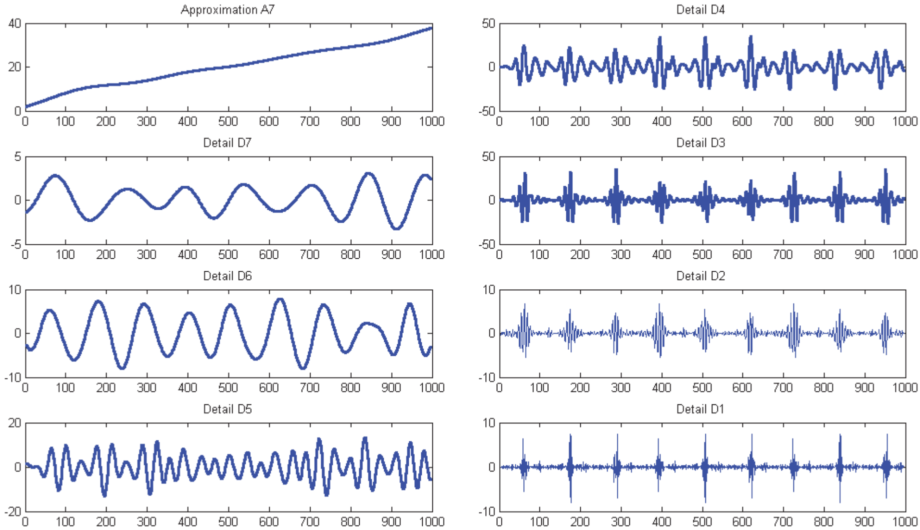

Fig. 6 – *The approximation A7 and details D1 – D7 of the ECG decomposition.*

Secondly, the results using ASWT filter, which is Fig. 8a shows the approximate A_7 results from Sym8 at level 7, and this approximate signal was passed through a proposed adaptive filter, and the output of the proposed adaptive filter is as shown in Fig. 8c. Fig. 8b illustrates the estimated noise between input and output. From this figure noted the BW liner noise exactly removed and low frequency content still at approximation A_7 without affected. Therefore, the reconstruction of the ECG signal using a new approximation A_7 and seven details D_1–D_7, was done using ISWT, and the output as shown in the Fig. 9.

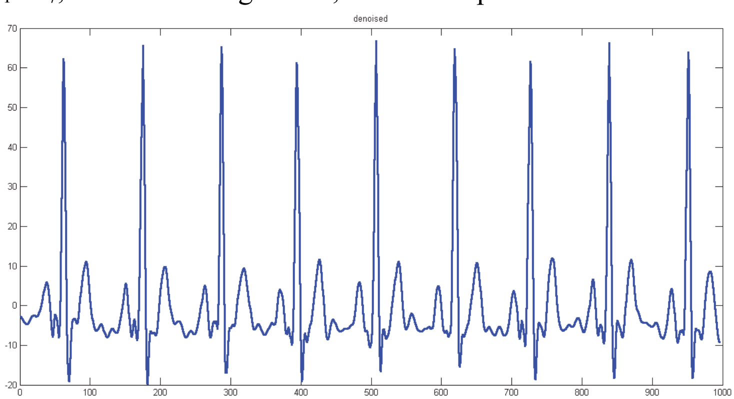

Fig. 7 – *Reconstructed ECG signal using WT without using adaptive filters.*

Patients with left precordial ST-segment depression in-Baghdad hospital mortality was nearly three times higher than the other group. Moreover, in patients with left precordial ST-segment depression in the anterolateral leads the patient has myocardial ischemia as shown in **Table 2.**

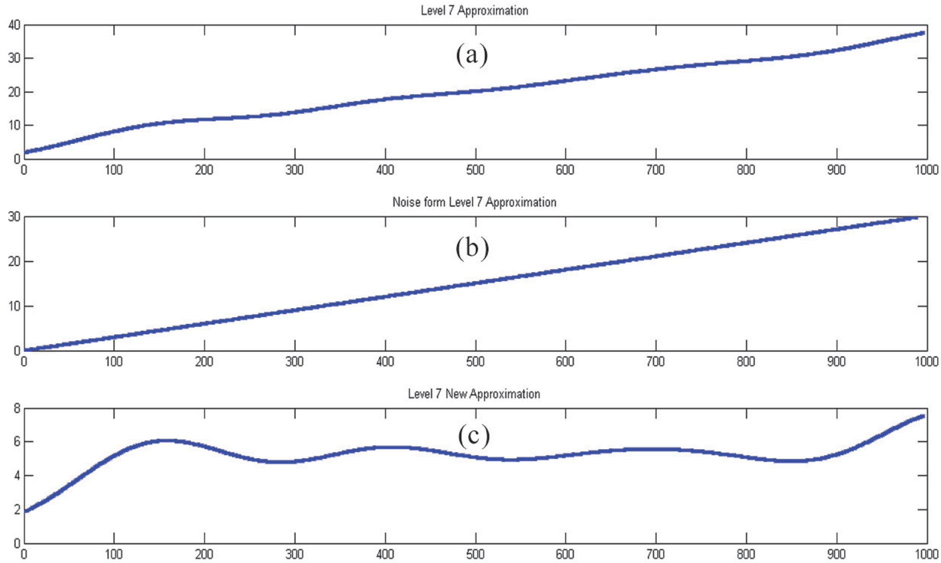

Fig. 8 – (a) *Noisy approximation A_7 input signal to the proposed adaptive filter,* (b) *Estimated noise between input and output, and* (c) *De-noising approximation A_7 output signal.*

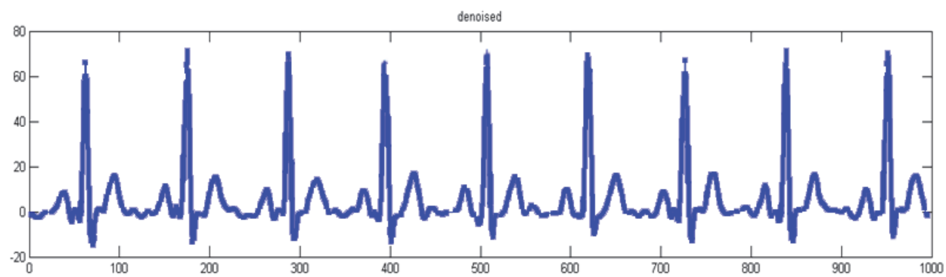

Fig. 9 – *Denoising ECG signal from our proposed filter.*

STR around 50% were reported in 387 (71.3%) patients in the left precordial ST-segment depression category and 516 (81.5%) patients with left precordial ST-segment depression (μ=0.016), indicating a less desirable mechanical reperfusion response in patients with this form of ECG changes.

Table 2
Adverse events in the chest

Real cases	Patients with ASWT-filtered precordial left S T-segment depression	Patients without ASWT filtered anxiety in the left precordial ST-segment	µ Value
Mortality	50 (12%)	17 (2.5%)	0.002
Pulmonary edema	44 (10.3%)	9 (1. 6%)	0.002
Ventricular arrhythmias	81 (11.8%)	76 (11.06%)	0.53
Repeat Myocardial Infarction (Re-MI)	22 (3.5%)	8 (1. 1%)	0.02
Complete heart block	83 (13.6%)	64 (9.8%)	0.35

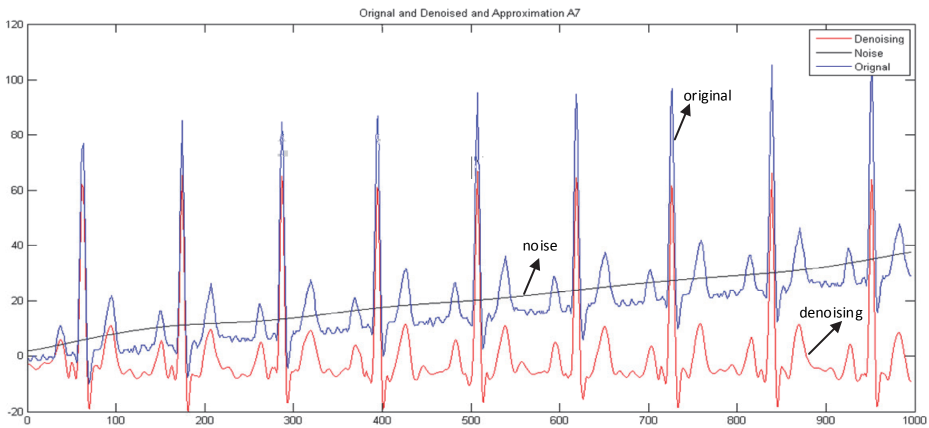

Fig. 10 – *Input, noise and output signals using SWT.*

Figs. 10 and 11 illustrate the original noisy ECG signal, estimated noise signal and de-noising ECG signal for both methods. From Fig. 10 notes that the output ECG signal is still affected by BW noise and produce an S-T segment distorted. While the Fig. 11 notes the clearly de-noising output ECG signal, and the ST segment is not affected by the filtering process. The evaluating a performance of the proposed ASWT was by using a SNR as the following:

$$SNR_{imp} = SNR_{out} - SNR_{in} \tag{8}$$

$$SNR_{imp} = 10\ log_{10}\left(\frac{\sum_i /x_d(i) - x(i)/^2}{\sum_i /x_n(i) - x(i)/^2} \right) \tag{9}$$

where x_d is the deionised signal, x denotes the original ECG, and x_n represents the noisy ECG signal.

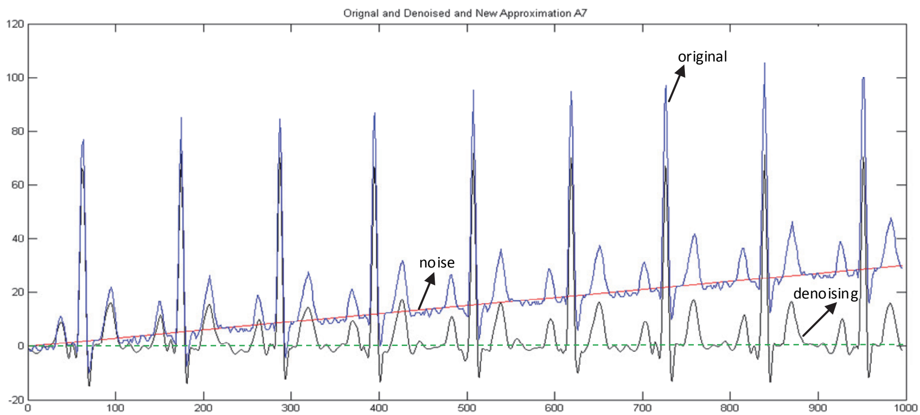

Fig. 11 − *Input, noise and output signals using ASWT.*

Table 3 shows the compares the improvement values between SWT and ASWT.

Table 3
SWT and ASWT denoising performance.

SNR Improved	Different ECG signals						
	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**	**Case 7**
SWT (dB)	6.5	5.5	6.1	6.0	6.4	6.2	6.6
ASWT (dB)	7.8	6.9	7.7	8.1	8.2	7.9	7.8

5 Conclusion

The proposed a new approach of combining the hybrid soft computing technique SWT along with adaptive filter called ASWT for BW noise removal from an ECG signals to minimize distortion of the S-T segment of an ECG signal by high sampling frequencies. This method represents a very effective filter for BW noise removal from an ECG signal at any sampling frequency without distorting the contents of the ECG signal, as it does not need for any computation process of reference point.

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