

## Artifact elimination in ECG signal using wavelet transform

Thanh-Nghia Nguyen, Thanh-Hai Nguyen, Van-Thuyen Ngo

Department of Industrial Electronics and Biomedical Engineering,  
HCMC University of Technology and Education, Vietnam

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### ABSTRACT

Electrocardiogram signal is the electrical activity of the heart and doctors can diagnose heart disease based on this electrocardiogram signal. However, the electrocardiogram signals often have noise and artifact components. Therefore, one electrocardiogram signal without the noise and artifact plays an important role in heart disease diagnosis with more accurate results. This paper proposes a wavelet transform with three stages of decomposition, filter, and reconstruction for eliminating the noise and artifact in the electrocardiogram signal. The signal after decomposing produces approximation and detail coefficients, which contains the frequency ranges of the noise and artifact components. Hence, the approximation and detail coefficients with the frequency ranges corresponding to the noise and artifact in the electrocardiogram signal are eliminated by filters before they are reconstructed. For the evaluation of the proposed algorithm, filter evaluation metrics are applied, in which signal-to-noise ratio and mean squared error along with power spectral density are employed. The simulation results show that the proposed wavelet algorithm at level 8 is effective, in which the with the “dmey” wavelet function was selected be the best based power spectrum density.

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### Corresponding Author:

Thanh-Hai Nguyen,

Department of Industrial Electronics and Biomedical Engineering,

HCMC University of Technology and Education,

1 Võ Văn Ngân, Linh Chiểu, Thủ Đức, Hồ Chí Minh, Vietnam.

Email: nthai@hcmute.edu.vn

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## 1. INTRODUCTION

Electrocardiogram (ECG) signals play an important role in diagnosing heart disease. The ECG signals are often collected by measuring the current from the heart activity using electrodes and have characteristics displayed on the paper or the screen [1]. In practice, ECG signal machines are designed to collect ECG signals from patients and then they can be stored on computers for diagnosing heart diseases. Therefore, ECG data can be used for analyzing and classifying types of heart diseases and this will produce accurate and fast results [2-4]. ECG signals collected from patient using electrodes can exist noise and artifact components such as power line interference (PLI), baseline wander (BW), electromyography (EMG), patient electrode motion, electrode popup or contact, and instrumentation effect [5-8]. Therefore, elimination of the noise and artifact components are a necessary task due to producing more accurate ECG signals during diagnostic process. For eliminating these components, transmutation and filters such as wavelet, finite impulse response (FIR) adaptive and others have been applied in recent years. The importance is that essential information of ECG signals after filtering can help for diagnosing heart diseases more accurately.

In recent years, methods of filtering noise in ECG signals such as FIR filters, infinite impulse response (IIR) filters, wavelet filters, adaptive filters, or other filters have been employed [9-12]. In practice, each filter for applying in each type of ECG signal has its own characteristics and so the effectiveness is different. With the effect of the transition band, one signal can be affected by the vicinity of the cutoff frequency, the FIR and IIR filters can be employed for filtering noise. If the process dynamics is linear, the adaptive filters can be utilized. In [13], Jacek Piskorowski proposed a second-order Q-varying digital IIR notch filter for reducing the unwanted sinusoidal interference of signals. Vivek Joshi et al. [14] presented an adaptive noise canceller, in which a modified particle swarm optimization was implemented to remove noise in ECG signal.

There have been a lot of different filters applied for ECG noise cancelling, in which wavelet algorithms with high-pass and low-pass filters were employed for eliminating noise and artifact [15-17]. The main advantages of using the wavelet algorithm can determine approximation and detail coefficients related to signal frequencies. Moreover, the wavelet algorithm can use different wavelet functions dependent on types of signals. In [18], Supriya Goel et al. applied five types of wavelet functions including daubechies, coiflet, haar, biorthogonal, and symmlet, and each wavelet function also has a lot of its sub-functions for calculating de-noise in ECG signals. In particular, the Daubechies family wavelets used in this paper have ten sub-functions (from db1 to db10) for the de-noise of ECG signal with the high performance.

Evaluating the filter performance of signals is important. In practice, there are different evaluation methods such as signal noise ratio (SNR) or mean square error (MSE) [19-22] related to the performance of the proposed filter dependent on types of filters. In this paper, a wavelet decomposition-filter-reconstruction (WDFR) algorithm is applied, in which ECG signals after decomposition are passed through the filter stage for completely eliminating noise and artifact before reconstructing them. Moreover, the filter evaluation methods such as SNR, MSE and the power spectral density (PSD) will be utilized for evaluating the performance of eliminating artifact and noise components using the WDFR. In particular, the PSD illustrates the power of ECG signal in the frequency domain related to presenting the power of one original ECG signal and one filtered ECG signal. In addition, the parameters of SNR and MSE describe the ratio of signal per noise along with the mean square error between one raw signal and one reconstruction signal. While, evaluation metrics will demonstrate the most suitable wavelet function for removing noise and artifact components in ECG signals.

## 2. PROPOSED METHOD

ECG signals collected on patients often have noise and artifact. Therefore, pre-processing and eliminating the noise and artifact in the ECG signals are important. In this research, a wavelet decomposition-filter-reconstruction (WDFR) algorithm is proposed for filtering the noise and artifact and then reconstructing the ECG signals, in which the ECG signals are pre-processed and normalized before decomposition, artifact elimination and reconstruction as shown in Figure 1.

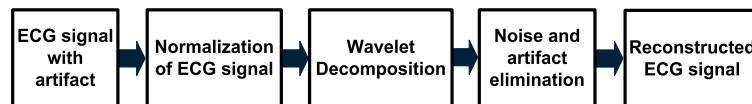


Figure 1. Block diagram of eliminating noise and artifact and reconstructing ECG signals

### 2.1. Artifact and noise analysis in ECG signal

In this paper, there are two types of ECG signals used in the WDFR algorithm, in which one type of ECG signals is collected from MIT-BIH database (MIT-BIH ECG signals) and another one is obtained at HCMUTE Lab (Lab ECG signals). The Lab ECG signals, which are directly collected on subjects, are the raw signals without pre-processing and they exist noise and artifact components. Therefore, eliminating the noise and artifact in the raw signals to produce the clean ECG signals is very important in diagnosis of heart diseases.

ECG signals often have different noise and artifact components such as power line interference (PLI), baseline wander (BW), and others. In particular, PLI has the frequency of 50 Hz or 60 Hz and the frequency of BW is less than 1 Hz [6]. Assume that  $x'[k]$  is a pure ECG signal, and  $v[k]$  is the BW noise component with the frequency of less than 1 Hz. Moreover,  $\tau[k]$  is the PLI noise component with the frequency of 50 Hz. Therefore, the ECG signal  $x[k]$  with noise and artifact is described as follows:

$$x[k] = x'[k] + v[k] + \tau[k] \quad (1)$$

when we apply the decomposition algorithm, the BW noise component will be the approximation component and its expression is described as follows:

$$a_m = a'_m + v[k] \tag{2}$$

in which  $a'_m$  is the approximation component of the pure ECG signal.

In addition, if the decomposition algorithm is employed with high level, the  $a'_m$  component is very small and the  $a_m$  can be the BW noise component  $v[k]$  only. With the PLI component  $\tau[k]$ , if the ECG signal has the maximum frequency of 180 Hz and the decomposition algorithm is employed at level 8, the PLI component  $\tau[k]$  can be the detail component  $d_2$  and its expression can be presented as follows:

$$d_2 = d'_2 + \tau[k] \tag{3}$$

where  $d'_2$  denotes the detail component at level 2.

The fourth stage in Figure 1 is the filter stage for completely eliminating noise and artifact. In particular, some of the obtained detail or approximation components considered as noise and artifact based on their frequency ranges in the ECG signal  $x[k]$  after the decomposition stage will be removed. The final stage is reconstruction block of the ECG signal after eliminating the noise and artifact. The filter for eliminating BW noise is expressed as follows:

$$\ddot{a}_m \approx a'_m \tag{4}$$

The ECG signals collected on patients are normalized by sampling at the frequency of 360 Hz using Nyquist's theorem, in which the maximum frequency of the ECG signals after sampling is 180 Hz. It means that the frequency of the ECG signals has the range of 0 Hz to 180 Hz applied to the WDFR algorithm for filtering noise and artifact and reconstructing.

### 2.2. Wavelet-decomposition-filter-reconstruction algorithm

To analyze an ECG signal with different frequency components, a wavelet-decomposition-filter-reconstruction (WDFR) algorithm is employed. In particular, the ECG signal after decomposing produces different frequency components, in which the frequency components containing the necessary information are retained and other frequency components such as noise and artifact will be eliminated. Therefore, the signals with the necessary information are reconstructed for diagnosing heart diseases. The framework of the WDFR algorithm consists of three stages of the decomposition, filter, and reconstruction as described in Figure 2.

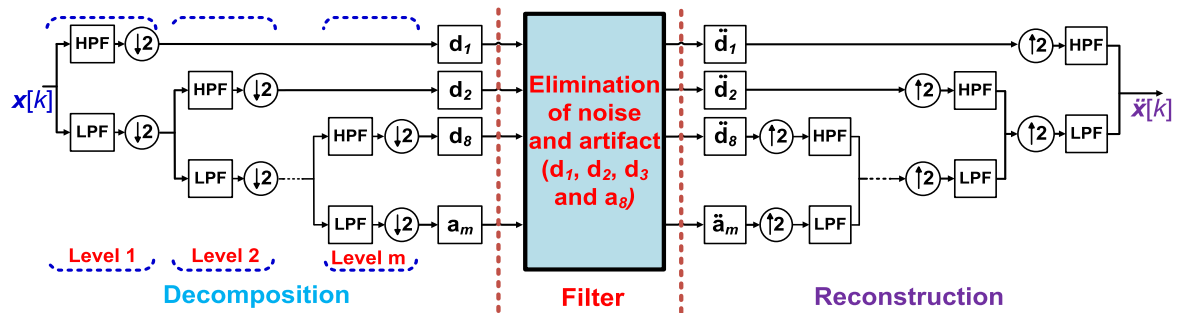


Figure 2. WDFR algorithm with three stages for removing noise and artifact in ECG signal

The WDFR algorithm with three stages is applied to decompose the ECG signal  $x[k]$  to produce approximation and detail coefficients corresponding to various frequency components for rebuilding the signal  $\tilde{x}[k]$  after filtering as shown in Figure 2. In particular, the decomposition stage is used to decompose the original ECG signal  $x[k]$  by passing through the high pass and low pass filters, in which the signal is downsampled by 2 to obtain the approximation and detail coefficients with the high and low frequency components. Therefore, the output of the high pass filter produces the high frequency component (detail) and that of the low pass filter is the low frequency component (approximation). It means that if this algorithm is employed at level

m, we will obtain the detail component  $d_m$  and the approximation component  $a_m$  and they are determined using the following (5) and (6) [23]:

$$d_m = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \quad (5)$$

$$a_m = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \quad (6)$$

in which,  $h[2n-k]$  describes the high pass filter, and  $g[2n-k]$  is the low pass filter. Hence, with applying the decomposition algorithm at level 8, the output of the algorithm will produce one approximation component  $a_8$  and eight detail components (from  $d_1$  to  $d_8$ ).

ECG signals can exist noises of power line interference (PLI), baseline wander (BW) and artifact and this can affect diagnostic results of heart diseases. Therefore, eliminating the noise and artifact has attracted researchers. In this paper, some approximation and detail components after the WDFR can be noise and artifact and filters are designed to eliminate these components as shown in Figure 2. With the WDFR algorithm, ECG signal after decomposition produces approximation and detail components which have the frequency ranges, in which there are the frequency ranges corresponding to PLI and BW noises and artifact. Therefore, low pass filters are designed to eliminate these frequencies before reconstruction of ECG signals. In particular, the approximate component is obtained by using the equation as follows:

$$\ddot{a}_m = \begin{cases} 0 & \text{if } f_{a_m} < f_a \\ a_m & \text{otherwise} \end{cases} \quad (7)$$

in which,  $f_a$  is the maximum frequency of the BW noise and  $f_{a_m}$  denotes the frequency of  $a_m$ .

Moreover, the detail components are obtained as follows:

$$\ddot{d}_m = \begin{cases} 0 & \text{if } f_{d_m} > f_a \\ d_m & \text{otherwise} \end{cases} \quad (8)$$

where  $f_a$  is a maximum frequency of ECG information frequency and  $f_{d_m}$  is frequency of  $d_m$ .

Therefore, the approximation ( $\ddot{a}_m$ ) and detail ( $\ddot{d}_j$ ) components obtained after eliminating the noise and artifact can be reconstructed to produce the pure ECG signal. In particular, the  $\ddot{a}_m$  component will pass through the low pass filter with upsampling by 2 and the  $\ddot{d}_j$  components will pass through the high pass filter with upsampling by 2 in order to reconstruct the filtered ECG signal. The expression for obtaining the filtered ECG signal is described as follows [23]:

$$\ddot{x}[k] = \ddot{a}_m + \sum_{j=0}^m \ddot{d}_j \quad (9)$$

in which  $\ddot{x}[k]$  denotes the reconstructed ECG signal.

### 2.3. Evaluation metrics

The proposed method for eliminating of noise and artifact should be evaluated for filter performance. In particular, the ratio of signal and noise is determined for evaluating the performance of the proposed WDFR method. Moreover, one wavelet function is effectively chosen in the WDFR algorithm based on the value of mean square error between filtered and original ECG signals and moreover it is chosen based on the similar shape of heartbeat.

#### 2.3.1. Filter performance

The performance of filters in WDFR algorithm will be evaluated by comparing the power spectral density (PSD) of raw ECG and reconstructed ECG signals. In particular, the spectral density of the ECG signal in the frequency domain shows the power of this signal corresponding the frequency [24]. Therefore, we can know the frequency component which is eliminated in the ECG signal by observing the PSD picture. Moreover, signal noise ratio (SNR) is utilized to evaluate the performance of the proposed WDFR method and calculated in dB as follows [23]:

$$SNR = 10 \log_{10} \left[ \frac{\sum_{i=1}^N \ddot{x}_i^2(k)}{[\sum_{i=1}^N \ddot{x}_i(k) - \sum_{i=1}^N \ddot{x}_i(k)]^2} \right] \quad (10)$$

in which,  $\ddot{x}(k)$  is the reconstructed ECG signal and  $N$  is length of one ECG signal (one heartbeat).

In this paper, SNR presents for the ratio between the ECG signal with noise components and the filtered signal in the WDFR algorithm. Therefore, the performance of the WDFR is evaluated based on the SNR value.

**2.3.2. Choice of wavelet function**

With PSD and SNR, mean square error (MSE) is applied to choose the suitable wavelet function for eliminating noise and artifact components in the ECG signal. In particular, the MSE describes the difference of the power between raw ECG and reconstructed ECG signals. Therefore, the MSE parameter is determined using the following (11) [9]:

$$MSE = \frac{1}{N} \sum_{i=1}^n [\hat{x}_i(k) - x_i(k)]^2 \tag{11}$$

**3. RESULTS AND DISCUSSION**

**3.1. Signal and wavelet function present**

In this research, six wavelet functions (“dmey”, “bior5.5”, “db4”, “sym1”, “bior1.3”, and “db1”) are proposed in the WDFR algorithm as shown in Figure 3. Assume that the shape of three wavelet functions is similar to that of one heartbeat [18] and the shape of six remaining wavelet functions is different from that of the heartbeat. All of the wavelet functions will be applied in the WDFR for removing noise and artifact components in ECG signal in order to choose the best wavelet function. One pure MIT-BIH ECG signal (code 234) with less noise and artifact was used to evaluate the effectiveness of the proposed method. Assume that noise and artifact components were added to the MIT-BIH ECG signal, particularly Signal Noise Ratio (SNR) of a sine wave with the frequency of 50 Hz and a DC signal is corresponding dB as shown in Figure 4.

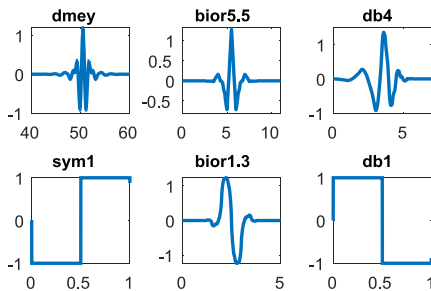


Figure 3. Six waves of the wavelet functions

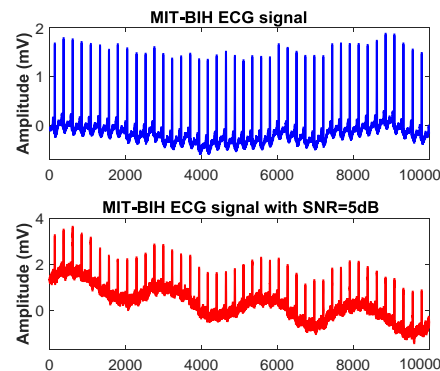


Figure 4. Pure MIT-BIH ECG signal (blue) and the MIT-BIH ECG signal with the noise and artifact (red)

**3.2. ECG signal decomposition and filter**

The MIT-BIH ECG signal with noise and artifact is decomposed to produce one approximation coefficient  $a_8$  and eight detail coefficients (from  $d_1$  to  $d_8$ ) as shown in Figure 5. Moreover, the MIT-BIH ECG signal is sampled at the frequency of 360 Hz and the frequency of the ECG signal has the range of 0 Hz to 180 Hz. After applying the wavelet decomposition, the frequency ranges of approximation and detail coefficients ( $a_8$  and  $d_1$  to  $d_8$ ) are obtained as described in Table 1.

Table 1. Frequency components after applying the wavelet decomposition algorithm

Level	Wavelet coefficient	Frequency Ranges (Hz)	Level	Wavelet coefficient	Frequency Ranges (Hz)
1	$d_1$	90 – 180	6	$d_6$	2.863 – 5.725
2	$d_2$	45 – 90	7	$d_7$	1.431 – 2.863
3	$d_3$	22.5 – 45	8	$d_8$	0.716 – 1.431
4	$d_4$	11.45 – 22.5	8	$a_8$	0 – 0.716
5	$d_5$	5.725 – 11.45			

From Table 1, filters in the WDFR algorithm are designed to eliminate noise and artifact components, in which the detail components ( $d_1$ ,  $d_2$ , and  $d_3$ ) and the approximation component ( $a_8$ ) are removed. In particular, the approximate  $a_8$  is considered as the BW noise and the detail  $d_1$  to  $d_3$  components are the PLI noise and artifact. Therefore, these component are removed and Figure 6 present the waveform of all component.

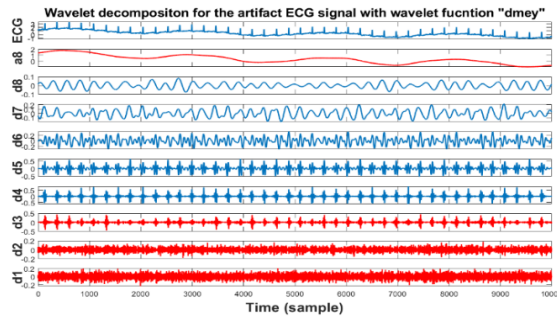


Figure 5. Waveforms of ECG signal with artifact and the approximate and detail coefficients ( $a_1$  and  $d_1$ , to  $d_8$ ) after applying the wavelet decomposition

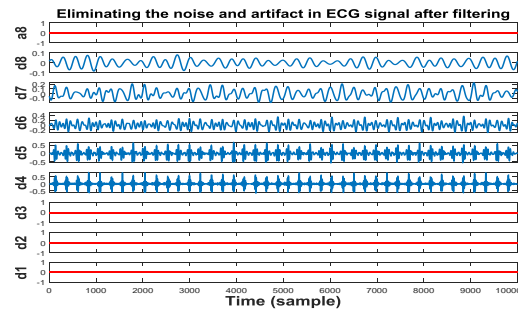


Figure 6. Waveforms of the approximate and detail coefficients ( $a_8$  and  $d_1$ , to  $d_8$ ) after applying the filter

### 3.3. ECG signal reconstruction

After applying the filter stage for eliminating noise and artifact in the ECG signal, the components of  $a_8$  and  $d_1$  to  $d_8$  are reconstructed to obtain the reconstructed ECG signal. In the reconstruction stage, assume that the WDFR algorithm with the wavelet function “dmey” at level 8 is applied for reconstructing the filtered ECG signal in the filter stage. In this paper, we used two types of ECG signals, including one MIT-BIH ECG signal and one Lab signal for comparing and evaluating the performance of the proposed method.

Figure 7 (a) shows the waveform of MIT-BIH ECG signal including noise and artifact value considered as SNR = 5 dB in blue color and the corresponding reconstructed ECG signal in red color is described in Figure 7 (b). For comparing between the MIT-BIH ECG signal with the noise and artifact and the reconstructed one, we can look at their power spectrum density (PSD) versus frequency as shown in Figure 8, in which for being easy to view, the ratio between Figure 8 (a) and Figure 8 (b) is different. It is clear that the noise and artifact in the reconstructed ECG signal are eliminated (Figure 8 (b)) compared to that of the ECG signal (Figure 8 (a)) at the frequency range of less 1 Hz.

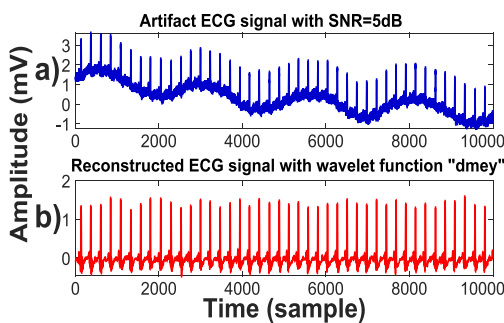


Figure 7. Waveforms of the MIT-BIH ECG with noise and the reconstructed ECG signals

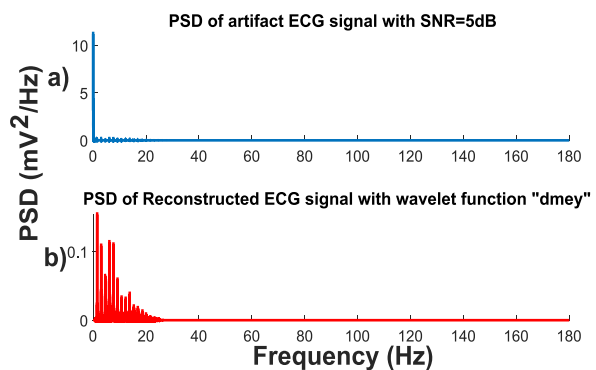


Figure 8. PSD of the MIT-BIH ECG with noise and the reconstructed ECG signals

In addition to using MIT-BIH ECG signals, we collected ECG signals at Biomedical Engineering Lab at HCMUTE, called Lab ECG signals, for evaluating noise artifact filter in the proposed WDFR algorithm. All of the Lab ECG signals used in this research are normalized by sampling at 360 Hz to produce the frequency range of 0 Hz to 180 Hz [25]. In particular, one Lab ECG signal and one the reconstructed one after using

the WDFR algorithm with the wavelet function "dmey" are presented in Figure 9 (a) (the raw Lab ECG signal) and Figure 9 (b) (the reconstructed signal). In addition, the raw Lab ECG signal (blue) with many noises, including peaks of the QRS complex in relation to BW noise. Therefore, the reconstructed Lab ECG signal shows to illustrate that the BW noise was removed due to the smoother peaks of the QRS complex. Furthermore, Figure 10 shows the PSD amplitudes of the raw Lab ECG signal and the reconstructed Lab ECG, in which the amplitude ratio between two signals is different. It is clear that Figure 10a shows the large spectrum amplitude at the frequency less than 1 Hz, while that of the reconstructed Lab ECG disappears due to removing the noise and artifact at the frequency components below 1 Hz and above 22.5 Hz as shown in Figure 10 (b).

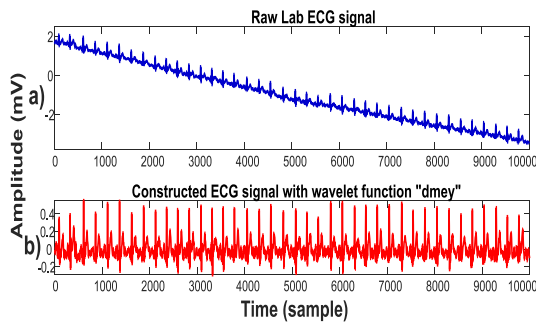


Figure 9. Waveforms of the Lab ECG and the reconstructed ECG signals

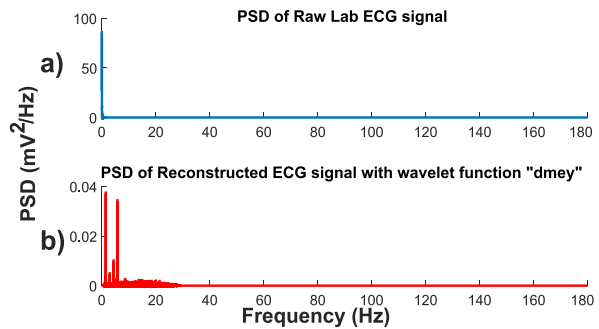


Figure 10. PSD of the Lab ECG and the reconstructed ECG signals

**3.4. Selection of wavelet function**

For the purpose of increasing the effectiveness of the proposed WDFR method, selecting one suitable wavelet function is performed. In particular, we applied six wavelet functions of “dmey”, “bior5.5”, “db4”, “sym1”, “bior1.3”, and “db1” to use in the WDFR for choosing the best one based on SNR and MSE values. In practice, the six wavelet functions were applied in WDFR algorithm for eliminating noise and artifact in ECG signals and then the SNR and MSE values were determined. In relation to the shape of waveforms of MIT-BIH ECG and Lab ECG signals, the waveforms of the ECG signals after reconstructing applied three wavelet functions of “dmey”, “bior5.5”, and “db4” are similar. While the remaining waveforms of the ECG signals using the wavelet functions of “sym1”, “bior1.3”, and “db1” are not nearly similar to that of the heartbeat. In particular, Figure 11 and Figure 12 show the MIT-BIH ECG signal, the reconstructed signals using two wavelet functions (“dmey” and “db1”), in which the waveform of the reconstructed signal using the “dmey” wavelet function is better than that of the waveform with the “db1”.

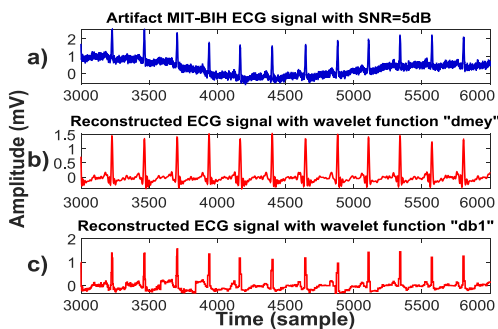


Figure 11. (a) Waveforms of the MIT-BIH ECG signal with noise, (b) the reconstructed ECG signals using “dmey”, (c) “db1”

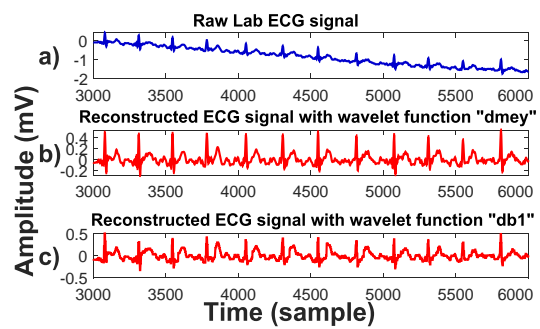


Figure 12. (a) Waveforms of the Lab ECG signal with noise, (b) the reconstructed ECG signals using “dmey”, (c) “db1” (c)

In addition to view the shape of ECG signals, SNR and MSE values related to the wavelet functions and noise levels are determined for selecting the best wavelet function. In particular, MIT-BIH ECG signals were added noise and artifact corresponding to SNR values (5 dB, 9 dB, 14 dB and 18 dB) of BW and PLI noise. After applying the WDFR algorithm with six wavelet functions, the SNR and MSE values were determined as shown in Table 2. In these results, the SNR value corresponding to the wavelet function "dmey" is larger compared to other wavelet functions, while the MSE value is smaller. This means that the "dmey" wavelet function is the best to apply in the WDFR algorithm for filtering and reconstructing MIT-BIH signals.

Table 2. SNR and MSE values with six different wavelet functions for the MIT-BIH ECG signal

$SNR_{raw}$	Wavelet functions											
	dmey		bior5.5		db4		sym1		bior1.3		db1	
	$SNR_{fil}$ (dB)	MSE	$SNR_{fil}$ (dB)	MSE	$SNR_{fil}$ (dB)	MSE	$SNR_{fil}$ (dB)	MSE	$SNR_{fil}$ (dB)	MSE	$SNR_{fil}$ (dB)	MSE
5 dB	8.850	0.520	8.698	0.617	8.696	0.617	8.562	0.618	8.558	0.615	8.215	0.619
9 dB	11.738	1.130	11.582	1.227	11.585	1.227	11.365	1.229	11.072	1.277	11.365	1.223
14 dB	15.618	2.009	15.416	2.203	15.427	2.203	15.184	2.200	14.889	2.286	15.184	2.300
18 dB	19.962	4.826	19.833	5.020	19.831	5.020	19.491	5.018	19.163	5.138	19.491	5.116

In similarity, SNR and MSE values of Lab ECG signals were calculated shown in Table 3. It is clear that the SNR and MSE values show to illustrate the WDFR algorithm using the "dmey" wavelet function in reconstructing the LAB ECG signal better. In particular,  $SNR_{fil}$  (26.778) is larger than other values and while  $MSE$  (3.009) is smaller than others

Table 3. Values of SNR and MSE of different wavelet functions for Lab ECG signal

	dmey	bior5.5	db4	sym1	bior1.3	db1
$SNR_{raw}$	0.0183	0.0168	0.0173	0.0160	0.0162	0.0160
$SNR_{fil}$	26.778	24.701	24.704	23.307	22.991	23.307
$MSE$	3.009	3.208	3.208	3.209	3.209	3.209

In [22], Atul and et al. used a Alexander fractional differential window filter for denoising MIT-BIH ECG signal and then SNR value is calculated for evaluating the effectiveness of the method. In particular, the results showed that the SNR is 19.609 dB for the MIT-BIH ECG signal (code 234). In this article, we applied the WDFR algorithm for eliminating noise and artifact components in two types of MIT-BIH ECG and Lab ECG signals and evaluated the effectiveness of the proposed method. The results show that both of the ECG signals employed by the WDFR algorithm wavelet function "dmey" at level 8 for reconstructing the ECG signals are effective through viewing their waveforms and SNR values, in which the SNR value of the MIT-BIH ECG signal (code 234) is 19.962 dB.

#### 4. CONCLUSION

In this article, the WDFR algorithm for eliminating noise and artifact components in ECG signals was applied, in which the WDFR algorithm at level 8 consists of three decomposition, filter and reconstruction stages. In particular, in the decomposition stage, we obtained one approximation component and eight detail components corresponding to their frequency ranges. Based on these frequency ranges, the noise and artifact components in the ECG signals were eliminated by using the filters and then the ECG signals after the filters were reconstructed to produce the reconstructed ECG signals without the noise and artifact. In this research, the SNR, and MSE values were calculated for evaluating the high performance of using the proposed WDFR method. In addition, the "dmey" wavelet function was chosen to be the best one of six wavelet functions based on PSD in the WDFR algorithm. The simulation results show to illustrate the effectiveness of the proposed WDFR method with the "dmey" wavelet function at level 8 in eliminating the noise and artifact components. In the future work, this proposed method may be applied for finding the QRS complex in ECG signals for classifying heart diseases using artificial intelligence systems

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