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Toward an Optimal Wavelet Filter and Decomposition Level for Noise Elimination of the ECG Signal

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Abstract: **The denoising process represents one of the most important preprocessing steps for Electrocardiogram (ECG) signal processing and assists the specialist in making the right diagnosis for the patient. Five wavelet filters (WFs) closest in morphology to the pattern of the ECG signal were nominated, and their performances were analyzed at different noise, and number of decomposition (No. Dec) levels to determine the optimum, among them for noise reduction task. These Filters are Daubechies 4 (DB4), Daubechies 6 (DB6), Coiflet 4 (Coif4), Symlet 6 (Sym6) and Symlet 8 (Sym8). The results of the standard ECG signals (downloaded from MIT-BIH) revealed that the DB6 filter with four decomposition levels is optimal for removing noise of the ECG signal in terms of three metrics "Mean Square Error" (MSE), "Output Signal to Noise Ratio" (SNRo), and "Correlation Coefficient Index" (CCI). In addition, a simple and efficient threshold rule was adapted to be used in the proposed method. The suggested approach was successfully applied to reduce the noise of the ECG signals recorded using a simple proposed electronic circuit. Finally, the performance of the introduced scheme was compared with that of the standard ECG equipment, the "Biocare iE300", and the outcomes were very close.**

Keywords: **electrocardiogram, wavelet denoising, wavelet filters; signal decomposition levels, thresholding**

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Contents

1. INTRODUCTION

An ECG is a graphical measurement of the electricity of the heart that indicates the prompt status for the health of the heart [1,2]. Therefore, it has been broadly utilized for diagnosing cardiovascular illness [3-6]. The traditional shape of the ECG signal with its most important distinguishing points is shown in **Fig. 1**. The noise cancellation is

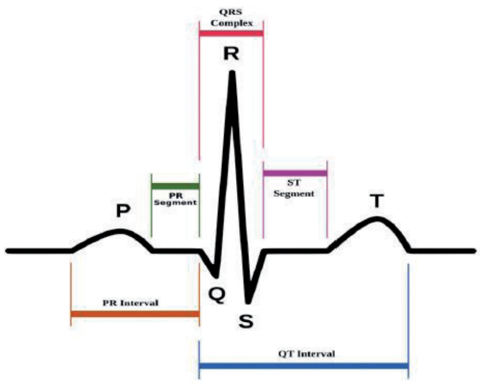

Fig. 1. *The principle components of a typical ECG waveform.*

one of the key processes that arise during the analysis of the heartbeat. The strength of the noise is low during the relaxation cases, while it becomes high when the person is under stress, and this makes the extraction of clinical information more difficult [7,8].

Different types of noise contaminate the ECG signal during acquisition and transmission, such as Electrode Movements (EM), Base-Line wanders (BL), Power-Line crosstalk (PL), Bad Electrode contact (BE), Inappropriate Measuring (IM) circumstances, and Electromyography (EMG) signals [9,10]. Most of the aforementioned types can be easily discarded using conventional filters, but the extraction of a clean heartbeat from an ECG signal that is corrupted with "Additive White Gaussian Noise" (AWGN) is a critical problem [11]. In spite of tremendous related works in this direction, there are numerous medical applications that need robust signal processing to abstract the clinical data in an efficient manner. Various approaches have been presented to improve the SNR of the noisy ECG signals [12-16]. The strategies that depend on Wavelet Transform (WT) surpassed the others because they showed good and stable performance in rejecting noise and exhibited high detection accuracy [17-20]. Nevertheless, which are the optimum WF and No. Dec levels for attaining these tasks remain prorated questions since it depends on the type and purpose of the specified application. This work attempts to answer the aforementioned question, specifically in the field of removing noise from the ECG signal using an effective methodology and a comprehensive analysis to determine the optimal WF and No. Dec levels. Also, this paper introduces a simple and efficient threshold rule. Finally, testing the reliability and robustness of the suggested scheme was performed using a simple, low-cost ECG acquisition system and standard ECG equipment, the "Biocare iE300".

2. A BRIEF OVERVIEW OF FILTERING BASED ON WAVELET

The aim of the wavelet filtering approach is to eliminate the AWGN $c(t)$ and to retrieve information signal $b(t)$. The idea is simply described in Eq. (1) [22]:

$$f(t) = b(t) + c(t) \tag{1}$$

The WT is an effective scheme with excellent time-frequency resolution, and it is perfect for signals of a non-stationary nature, such as ECG [3]. The WT divides the ECG signal into Detail coefficients (Dc) and Approximation coefficients (Ac) that can be formulated as the following [3]:

$$Dc[k] = \sum_{k=-\infty}^{\infty} f(s)H(2k-s), \tag{2}$$

$$Ac[k] = \sum_{k=-\infty}^{\infty} f(s)L(2k-s), \tag{3}$$

where s is a sampling data point, k is the No. Samples, $f(s)$ is the signal contaminated with noise, $H(2k - s)$ and $L(2k - s)$ are high-pass and low-pass filters, which alter based on the type of wavelet function [3]. The WT permits the abstraction of a specific frequency band from the signal. **Fig. 2** demonstrates the three levels of decomposition into Ac and Dc.

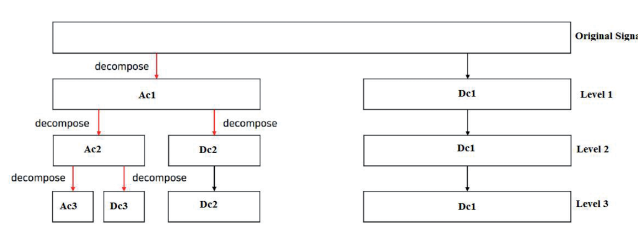

Fig. 2. *The three levels decomposition scheme.*

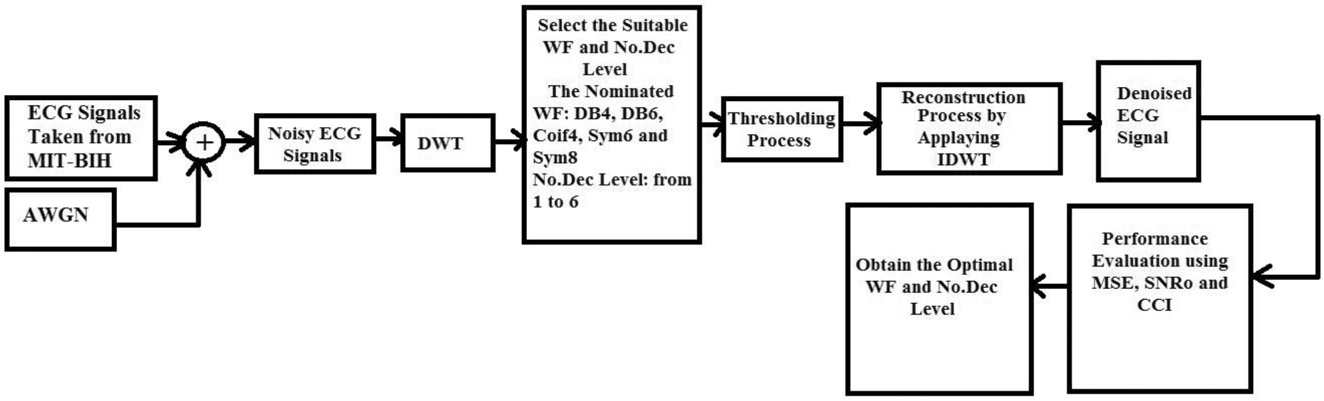

Fig. 3. *Block diagram of the investigative phase.*

The WF consists of scaled and dilated paradigms of the scaling function α(*j*) and wavelet function β(*j*) [23]. The low-pass coefficients and high-pass coefficients are associated with α(*j*) and β(*j*), respectively, as illustrated in Equations (4)-(6) [23]:

$$L(H) = (-1)^k H(1-k), \tag{4}$$

$$\alpha(2j-k) \rightarrow \alpha(j) = \sum\nolimits_k H(k)\sqrt{2}, \tag{5}$$

$$\beta(2j-k) \rightarrow \beta(j) = \sum\nolimits_k L(k)\sqrt{2}. \tag{6}$$

The high-pass and low-pass filters are featured parameters for each WF. Therefore, specifying the WF and No. Dec level has a significant impact on the performance of the denoising process.

3. SUGGESTED APPROACH

The proposed framework comprises two phases: the investigative phase, based on real standard ECG signals taken from MIT-BIH [24], and the verification phase, based on ECG signals recorded using the suggested Simple-design, Low-cost Acquisition system (SLA) and ECG signals collected using the standard ECG equipment, "Biocare iE300".

3.1. Investigative Phase

This phase aims to investigate to answer the following questions: The first is: what is the optimal WF? The second is: what is the optimal No. Dec level for minimizing the noise of the ECG signals? The steps of the investigative phase are displayed in **Fig. 3**. The real, standard ECG signals (46 records) from MIT-BIH were utilized and the AWGN was added to them to obtain the noisy ECG signals. Three levels of AWGN (15 dB, 20 dB, and 25 dB) were generated and added to the original signals using the MATLAB program. After that, the Discrete Wavelet Transform (DWT) was applied to the noisy ECG signals. Five filters whose patterns are the closest to the morphology of the ECG signal were nominated to compete with each other to discover the optimal one for the process of filtering ECG signals. In order to get the ideal reconstruction (as possible), only orthogonal filters were examined. Furthermore, the orthogonal property allows inexpensive calculations. To achieve the aforementioned factors, the following filters (as demonstrated in **Fig. 4**): DB4, DB6, Coif4, Sym6, and Sym8 put under investigation. The No. Dec levels varied from 1 to 6.

At each level, the signal under the test is subjected to a bank of filters, as described in section 2. The next step is the thresholding

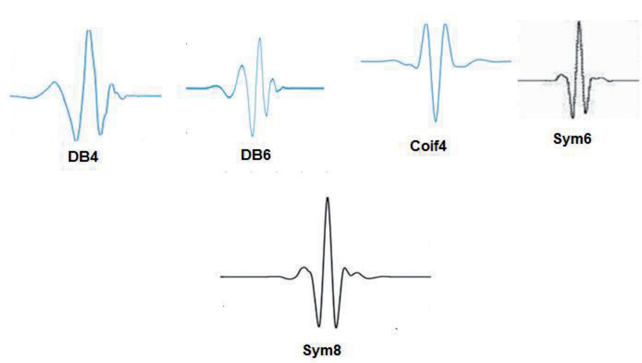

Fig. 4. *The patterns of the nominated wavelets.*

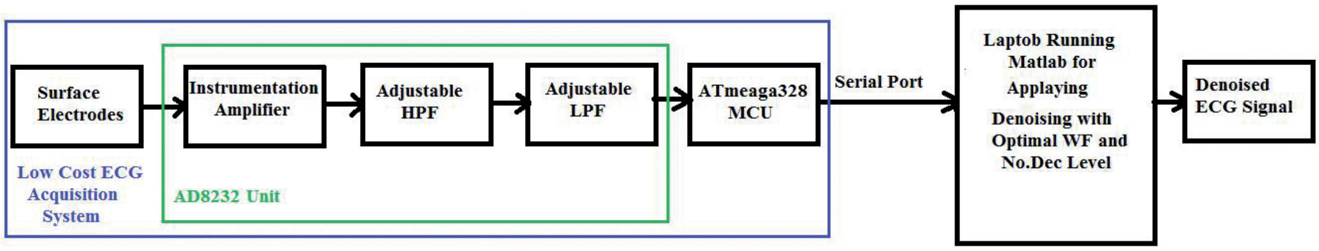

Fig. 5. *Block diagram of the SLA.*

process. There are two main thresholding methodologies, Soft thresholding (S_{th}) and Hard Thresholding (H_{th}). Many works [11,25,26,27] have proved the advantage of S_{th} in obtaining a smoother signal, as opposed to H_{th}, which causes discontinuities in the signal. Therefore, the S_{th} defined in Eq. (7) [28] is used in this paper.

$$S_{th}(D_c) = sign(D_c)(|D_c| - t_h)\ for\ |D_c| > t_h,\quad and\ 0\ for\ |D_c| \le t_h, \tag{7}$$

where t_h is the threshold value.

Different threshold determination schemes have been suggested in the literature [14 and 29]. The universal approach (given in Eq. (8)) was used in this study for the straightforwardness of its calculations and its robust performance [22, 27].

$$t_h = ESD\sqrt{2\log(No.Samples)},\quad ESD = MAD(D_c)/0.6745, \tag{8}$$

were ESD is the Estimation for the Standard Deviation of noise; MAD (Dc) is the Median Absolute Deviation for the Dc of the WT.

The thresholding process is followed by the reconstruction process, which is the inverse of the DWT, and then the denoised ECG signal is obtained. Finally, the performance was quantified using SNRo, MSE, and CCI. The WF and No. Dec levels that satisfied the highest SNR, CCI and lowest MSE were specified as the optimum.

3.2. Verification Phase

This phase includes the design of the SLA. The design of the SLA is composed of three units: surface electrodes that are placed on the human chest to record the signals, AD8232, and ATmega328 microcontroller as illustrated in **Fig. 5**. The AD8232 unit includes three components: Instrumentation Amplifier (IA) for signal amplification, amenable HPF for motion artifacts rejection, and amenable LPF for line interference cancellation. The board of the ATmega328 is equipped with a crystal of 16 MHz and 10 bits ADC. The f_s = 360 Hz. The computer, which runs the MATLAB R2020a is provided with digital signals via a USB port. Twenty signals (10 from males and 10 from females) were recorded. **Fig. 6** shows the collection process of ECG from a healthy male. The MATLAB 2020a program implements the denoising scheme with the optimal WF and No. Dec levels.

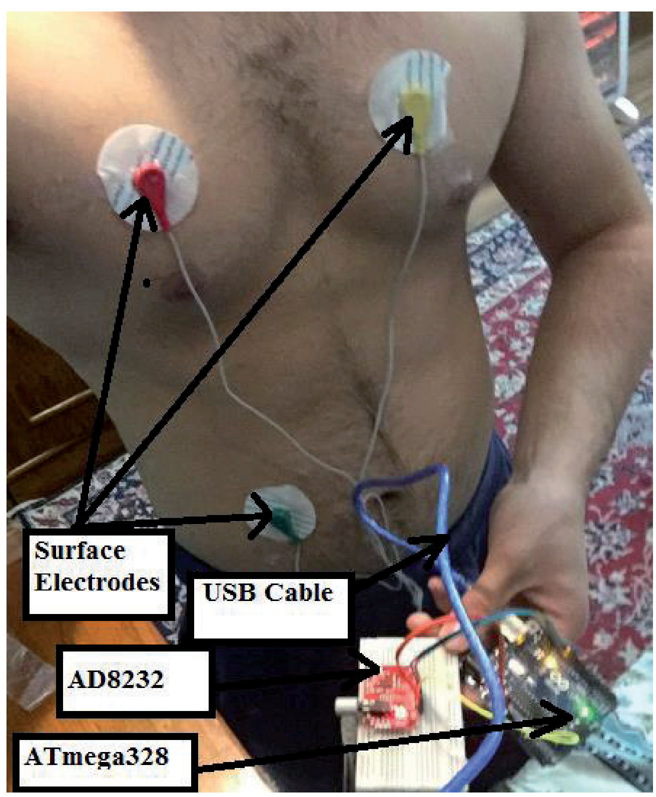

Fig. 6. *Recording ECG from a male.*

4. RESULTS AND DISCUSSION

The three main assessments metrics for specifying the optimal WF and No. Dec levels are the MSE, SNRo, and CCI, which are evaluated by equations (9), (10), and (11) respectively [2, 22]:

$$MSE = \sum_{p=1}^{z} \frac{1}{z}(v(p) - v^{-}(p))^2, \tag{9}$$

$$SNR = 10\log\left(\frac{\sum_{p=1}^{z}(v(p))^2}{\sum_{p=1}^{z}(v(p) - v(p)^{-})^2}\right), \tag{10}$$

$$CCL = \\ = \frac{\sum_{p=1}^{z}(v(p) - mean[v(p)])(v^{-}(p) - mean[v^{-}(p)])}{\sqrt{\sum_{p=1}^{z}(v(p) - mean[v(p)])^2 (v^{-}(p) - mean[v^{-}(p)])^2}}, \tag{11}$$

where $v(p)$ is the original signal, $v^{-}(p)$ is the denoised (filtered signal).

The comprehensive average results for each WF at different AWGN levels with various No. Dec levels are illustrated in **Tables 1-5**.

Table 1

The performance of the DB4 WF

Wavelet Filter: DB4								
AWGN with SNR=15 dB			AWGN with SNR=20 dB			AWGN with SNR=25 dB		
No. Decomposition Level	MSE	SNRo (db)	No. Decomposition Levell	MSE	SNRo (db)	No. Decomposition Level	MSE	SNRo (db)
1	0.1339	17.4668	1	0.0862	21.2932	1	0.0620	24.1475
2	0.1307	17.6727	2	0.0713	22.9378	2	0.0417	27.5974
3	0.1117	19.0418	3	0.0712	22.9454	3	0.0411	27.7129
4	0.1032	19.7304	4	0.0634	23.9631	4	0.0482	26.3364
5	0.1495	16.5063	5	0.1050	19.5767	5	0.0860	21.3083
6	0.1861	14.6066	6	0.1545	16.2236	6	0.1421	16.9466

Table 2

The performance of the DB6 WF

Wavelet Filter: DB6								
AWGN with SNR=15 dB			AWGN with SNR=20 dB			AWGN with SNR=25 dB		
No. Decomposition Level	MSE	SNRo (db)	No. Decomposition Levell	MSE	SNRo (db)	No. Decomposition Level	MSE	SNRo (db)
1	0.1248	18.0727	1	0.0803	21.9010	1	0.0674	23.4212
2	0.1232	18.1856	2	0.0670	23.4787	2	0.0494	26.1263
3	0.1042	19.6429	3	0.0597	24.4772	3	0.0389	28.2014
4	0.0929	20.6392	4	0.0535	25.4364	4	0.0403	27.8944
5	0.1856	14.6266	5	0.1480	16.5951	5	0.1375	17.2360
6	0.1999	13.9816	6	0.1670	15.5467	6	0.1579	16.0349

Table 3

The performance of the Coif4 WF

Wavelet Filter: Coif4								
AWGN with SNR=15 dB			AWGN with SNR=20 dB			AWGN with SNR=25 dB		
No. Decomposition Level	MSE	SNRo (db)	No. Decomposition Levell	MSE	SNRo (db)	No. Decomposition Level	MSE	SNRo (db)
1	0.1265	17.9599	1	0.0877	21.1427	1	0.0496	26.0950
2	0.1155	18.7516	2	0.0743	22.5788	2	0.0416	27.6133
3	0.1096	19.2016	3	0.0702	23.0692	3	0.0406	27.8317
4	0.0997	20.0242	4	0.0618	24.1855	4	0.0406	26.8911
5	0.1353	17.3728	5	0.1148	18.8027	5	0.0895	20.9625
6	0.1503	16.4603	6	0.1377	17.2243	6	0.1116	19.0493

Table 4

The performance of the Sym6 WF

Wavelet Filter: Sym6								
AWGN with SNR=15 dB			AWGN with SNR=20 dB			AWGN with SNR=25 dB		
No. Decomposition Level	MSE	SNRo (db)	No. Decomposition Levell	MSE	SNRo (db)	No. Decomposition Level	MSE	SNRo (db)
1	0.1258	18.0030	1	0.0894	20.9767	1	0.0634	23.9532
2	0.1186	18.5218	2	0.0776	22.2000	2	0.0502	25.9825
3	0.1065	19.4558	3	0.0732	22.7065	3	0.0413	27.8049
4	0.1004	19.9659	4	0.0653	23.6982	4	0.0407	27.6891
5	0.1347	17.4149	5	0.1111	19.0896	5	0.0927	20.6600
6	0.1517	16.3785	6	0.1357	17.3506	6	0.1205	18.3783

Table 5

The performance of the Sym8 WF

Wavelet Filter: Sym8								
AWGN with SNR=15 dB			AWGN with SNR=20 dB			AWGN with SNR=25 dB		
No. Decomposition Level	MSE	SNRo (db)	No. Decomposition Levell	MSE	SNRo (db)	No. Decomposition Level	MSE	SNRo (db)
1	0.1339	17.4668	1	0.0902	20.8939	1	0.0658	23.6371
2	0.1307	17.6727	2	0.0739	22.6253	2	0.0514	25.7737
3	0.1117	19.0418	3	0.0714	22.9212	3	0.0406	27.8189
4	0.1032	19.7304	4	0.0600	24.4331	4	0.0414	27.6697
5	0.1495	16.5063	5	0.1164	18.6835	5	0.0988	20.1048
6	0.1861	14.6066	6	0.1440	16.8333	6	0.1267	17.9459

In general, for each WF, the fourth decomposition level introduces the optimum results at very high noise (AWGN with SNR = 15 dB) and high noise (AWGN with SNR = 20 dB) environments, while the third decomposition level exhibits the best results at medium noise (AWGN with SNR = 25 dB) environments. The optimal WF achievement

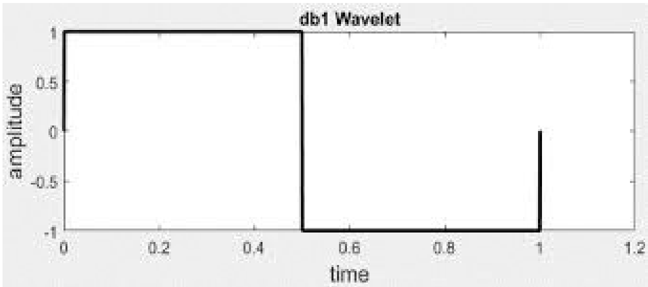

Fig. 7. *The DB1 (Haar) WF.*

Table 6
The average performance of the nominated WFs in terms of CCI at all noise environments with No. Dec level = 4

Wavelet Filter (WF)	Correlation Coefficient Index (CCI)
DB4	0.9829
DB6	0.9847
Coif4	0.9832
Sym6	0.9827
Sym8	0.9840

is recorded for DB6. Here it is worth noting that the WFs were carefully nominated (as mentioned in section 3.1) to optimize the filtering process; in other words, all WFs have good and fairly close performance, and the study aims to discover the optimal WF. The wise choice for the WF grantees getting a good quality of the reconstruction, for instance, the selection of DB1 (Haar) is considered a bad decision because its shape (as displayed in **Fig. 7**) is very dissimilar to ECG, and thus worse reconstruction is obtained (much clinical information are lost) as appeared in **Fig. 8**. Since the difference is not significant between the third and fourth levels for medium noise environments, we have concluded that the No. Dec level = 4 is generally optimal for all noise environments. To enhance the produced results in terms of MSE, SNRo, a third assessment metric (CCI) was determined for each WF and it gave the same indication.

Since it agrees with the results of MSE and SNRo and to avoid the enormity of the results, only those cases with No. Dec level = 4 are shown in **Table 6**. Referring to the achievement of the WFs nominated in this study, DB6 is ranked first at all noise environments; for example, at high noise environments with No. Dec level = 4 (MSE = 0.0535, SNRo = 25.4364 dB and CCI = 0.9847) followed by Sym8 (MSE = 0.0600, SNRo = 24.4331 dB and CCI = 0.9840) then Coif4 (MSE = 0.0618, SNRo = 24.1855 dB and CCI = 0.9832), DB4 (MSE = 0.0634, SNRo = 23.9631 dB and CCI = 0.9829), and finally Sym6 (MSE = 0.0653, SNRo = 23.6982 dB, CCI = 0.9827). The detailed average results are demonstrated in the Tables 1-6.

Figures 9-11 demonstrate the attainment of denoising the ECG using the DB6 at various noise environments.

After conducting several experiments, Eq (8) has been developed with retaining its simplicity and improving the results. The improved threshold equation ($Th_{m,n}$) is defined in Eq. (12):

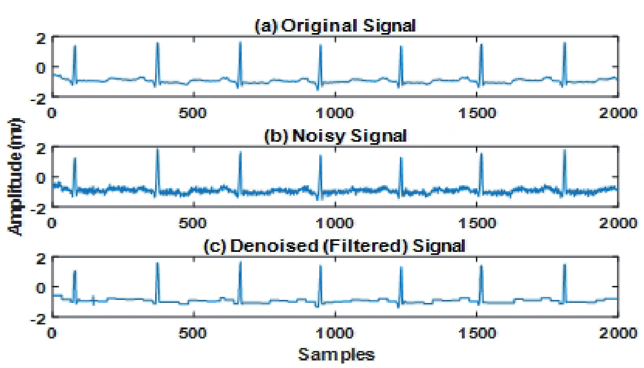

Fig. 8. *Denoising ECG using DB1 WF with No. Dec level = 4 in a high noise environment.*

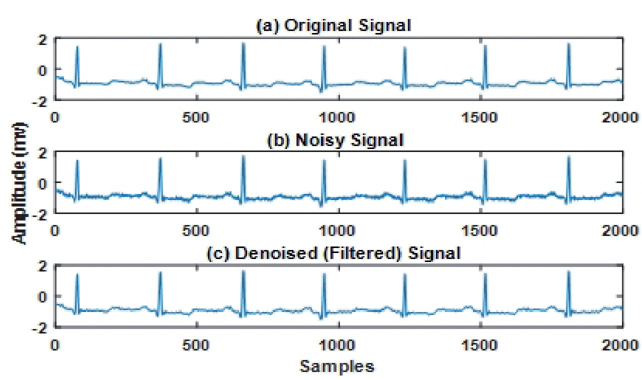

Fig. 9. *Denoising ECG using DB6 WF with No. Dec level = 4 in medium noise environment.*

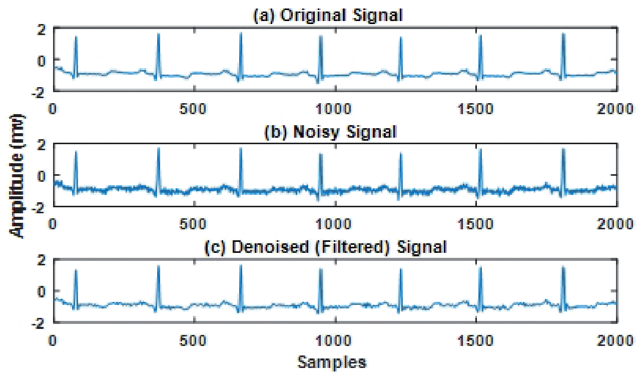

Fig. 10. *Denoising ECG using DB6 WF with No. Dec level = 4 in a high noise environment.*

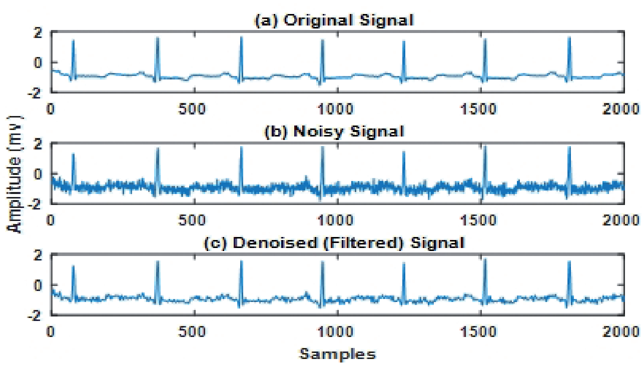

Fig. 11. *Denoising ECG using DB6 WF with No. Dec level = 4 in a very high noise environment.*

$$Th_{m,n} = 0.75\left(\frac{M}{N}\right)\frac{ESD_{n^*}\sqrt{2\log(No.Samples)}}{O_{m,n}+i}, \quad (12)$$

$n = 1, 2, \ldots, m,$

where $O_{m,n} = 2^{(M-(N/M))}$, M is the largest decomposition level, and N is the level at which the thresholding process is performed.

This paper introduces an adjustment factor (M/N). The adjustment factor M/N reduces progressively in response to the rise in No. Dec levels. This factor highlights the effect of the lower levels that are advantageous in the ECG signal by maximizing its value at the lower levels. Moreover, with this factor, the finest value of the tuning parameter (i) can improve the performance of the filter; this guarantees that the filtering is more effective; for instance, the achievements of the DB6 with No. Dec level = 4 using the $Th_{m,n}$ at very high noise environment are MSE = 0.0502, SNRo = 24.9810 dB, and CCI = 0.9861.

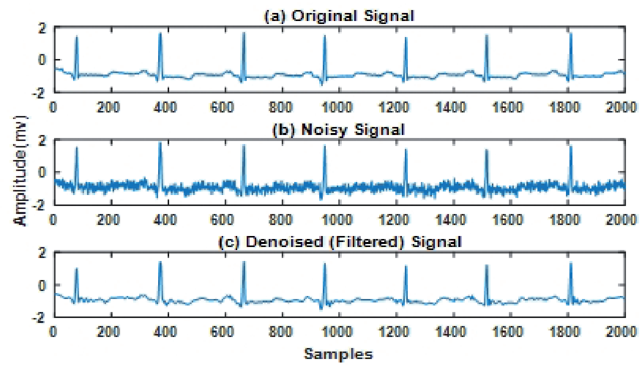

Fig. 12. *Denoising ECG using DB6 WF with No. Dec level = 4 using the $Th_{m,n}$ in a very high noise environment.*

Fig. 12 shows that the filtering process using the $Th_{m,n}$ is smoother, and the signal is reconstructed with less noise and this makes it closer to the original signal.

Based on the aforementioned analysis and the results from the investigative phase, the denoising approach using DB6-WF with No. Dec level = 4 was applied to the real ECG signals that were recorded by the SLA, which was designed in the verification phase. Excellent results were obtained, and this reflects the efficiency of the proposed framework in minimizing the noise of the ECG signals. **Fig. 13** illustrates a sample of applying this approach to the ECG signal recorded from a young male. For more testing of the reliability of the introduced denoising method, twenty ECG signals were collected using standard ECG equipment (Biocare iE300, specifications in [30]). The collected signals were saved (with and without applying the filtering option) into a USB flash memory

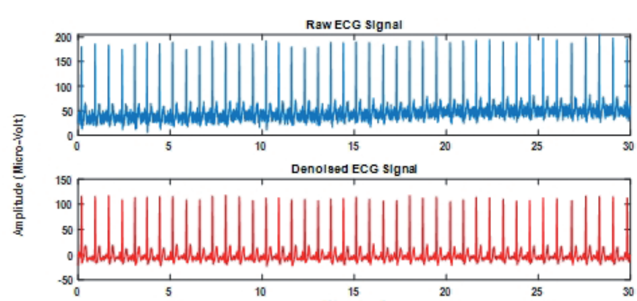

Fig. 13. *Sample of denoising ECG signal captured by SLA using the DB6 WF with No. Dec level = 4 and the $h_{m,n}$.*

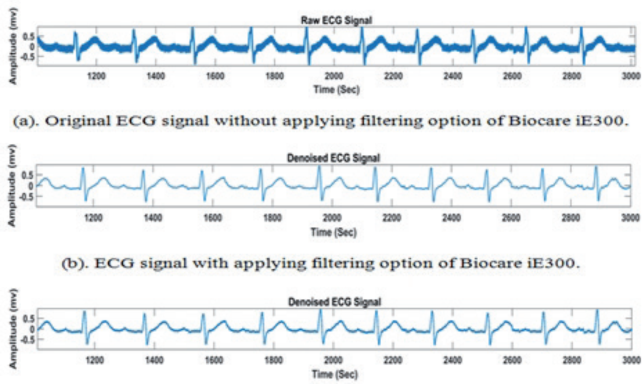

Fig. 14. *A sample of the visual performance comparison between Biocare iE300 and the proposed method.*

and then exported into MATLAB R2020a. The performance of the suggested denoising method is close to that of the Biocare iE300, as demonstrated in **Fig. 14**.

5. CONCLUSION

Noise that contaminates the ECG signal during its recording or transmission is an inevitable dilemma. This paper offered an excellent methodology based on WT for eliminating the noise of ECG signals by selecting the most appropriate WF and No. Dec levels; in addition, a simple and effective threshold calculation scheme was adapted to optimize the denoising process. The results revealed that the optimal WF was the DB6 with four levels of decomposition for both standard ECG signals taken from MIT-BIH and the ECG signals recorded using the suggested SLA and the standard ECG equipment, the "Biocare iE300". The filtered signal conserves critical features that can be utilized efficiently for medical diagnostic tasks.

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