Design and FPGA Implementation of an Efficient Architecture for Noise Removal in ECG Signals Using Lifting-Based Wavelet Denoising

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***Abstract*—Noise removal is the most crucial pre-processing step for present-generation biomedical wearable electrocardiogram (ECG) patches and devices to provide efficient detection and monitoring of cardiac arrhythmias. This paper proposes a hardware-efficient and multiplier-less FPGA-based ECG noise removal architecture based on lifting-based wavelet denoising that employs a universal threshold level-dependent function in combination with soft thresholding to produce a noise-free ECG signal. The paper also proposes a modified lifting-based discrete wavelet transform (DWT) algorithm that is multiplier-less and provides a one-step equation for the calculation of the forward output coefficients and the inverse output coefficients. Since a comparator circuit is a very complicated circuitry in VLSI implementation, an optimized median calculation and soft thresholding block with no compare operations for wavelet-based thresholding is proposed. The ECG data is collected from the MIT-BIH arrhythmia database and the ECG noises from the MIT-BIH noise stress database. The proposed denoising technique for the ECG signal is tested on MATLAB which achieves an average improvement in SNR of 7.4 dB and an MSE of 0.0206. The FPGA implementation is performed on the Nexys 4 DDR board, and the proposed wavelet-based denoising architecture results in lower hardware utilization and a relatively high operating frequency of 166 MHz when compared to existing ECG denoising architectures.**

Keywords—Field programming gate array, wearable ECG devices, ECG noise removal, lifting-based discrete wavelet transform, soft thresholding

I. INTRODUCTION

The electrocardiogram (ECG) is a non-invasive standard technique for capturing electrical impulses in the heart using 12-leads, and it is also the most effective medical tool for determining heart health. In today's generation of medical advancements, wearable and remote biomedical electronic devices like ECG patches or devices have simplified the standard method of acquiring ECG in care units to at-home ECG data monitoring, detecting abnormal heart rhythms and cardiac arrhythmias. Such devices employ a range of signal-processing techniques to provide real-time ECG monitoring and efficient arrhythmia detection. Wearable ECG devices or mobile cardiac telemetry (MCT) patches are mostly small portable devices that require hardware-efficient signal-processing algorithms to provide cardiac monitoring. The most significant steps in such ECG devices are noise removal and the detection of QRS and R-peaks to provide any kind of cardiac arrhythmia detection. The noises associated with an ECG signal can be categorized into two parts, the first being the high-frequency powerline interferences (PLI) with a frequency of 50-60 Hz and the second being the low-frequency noises namely the baseline wander (BW) with a frequency range of 0.5-0.6 Hz and the motion artifacts (MA) with a frequency range of 10-30 Hz. The removal of the ECG noises plays an important role in pre-processing as these noises can lead to misinterpretation of the ECG features which can further degrade the efficiency of arrhythmia detection.

Related research work on ECG noise removal includes different signal processing techniques like conventional filtering using low-pass, high-pass, and notch filters [1], adaptive filters [2], empirical mode decomposition (EMD) [3], and wavelet transform [4]. Conventional filtering techniques suffer from signal leakage, resulting in the loss of ECG features in the stop band. The adaptive filters work by eliminating noise with a reference signal that is correlated with the original signal. The requirement of the reference signal is not very suitable for real-time applications, and adaptive filtering techniques suffer from high computational complexity due to their feedback paths. EMD suffers from the mode-mixing problem, which occurs when a particular decomposition level contains frequency components from other decomposition levels, making it difficult to estimate the frequency range of the decomposition levels [5]. Denoising using wavelet transform works well not only with the removal of all kinds of noises but also with simultaneous R-peak and QRS detection. The output signal from the above-mentioned denoising techniques especially the adaptive filters and conventional filtering requires complex signal processing techniques that needs extra processing steps like derivative, squaring, etc to intensify and detect R-peak and the QRS complex in the ECG signals. The R-peak detection technique in [6] uses five stages including pre-processing using a band-pass filter and subsequent processing with differentiation and Shannon energy envelope. The resulting hardware utilized is extremely high because of the use of so many signal-processing techniques. Kalman filtering and adaptive thresholding are used for QRS complex detection which results in a good detection rate but utilizes large amounts of registers and LUTs [7]. In terms of noise-removal in ECG signals, the wavelet packet transform and wavelet-based thresholding are used in [4] and implemented using MATLAB Simulink. Area overhead is quite high in [4] since the noise-removal architecture is not optimized and includes complex arithmetic operations. On the other hand, the use of the canonical signal decomposition (CSD) technique to implement the DWT filter in [8] results in zero multipliers and low resource utilization. ECG signal denoising using a wavelet-based thresholding technique will offer an efficient pre-processing stage with efficient hardware requirements.

This paper aims to design an efficient, and optimized wavelet-based noise-removal architecture for the ECG signal that can be used as a pre-processing step for MCT and wearable cardiac monitoring devices. The proposed noise-removal algorithm is simulated in MATLAB which results in an average improvement in SNR of 7.4 dB and an average MSE of 0.0206. The resulting architecture from the proposed noise-removal algorithm is implemented in VIVADO using Verilog-HDL and verified on the Nexys 4 DDR FPGA board. The proposed FPGA-based ECG noise-removal architecture consists of a modified lifting-based forward and inverse DWT algorithm for signal decomposition that is multiplier-less, a median calculation block that employs an optimized and multiplier-less sorting algorithm to calculate the threshold value using the universal level-dependent technique and a soft-thresholding technique that does not involve any compare operations. The CSD method is adopted to make the complete architecture multiplier-less and hardware-efficient.

The remaining paper is arranged as follows. A description of the lifting-based DWT and wavelet-denoising technique is shown in Section 2. The proposed MATLAB algorithm for the ECG signal noise-removal using the wavelet denoising technique and the FPGA implementation of the denoising architecture are described in Section 3. Section 4 describes the results obtained from the MATLAB and FPGA implementation and their comparisons with the existing noise-removal techniques for the ECG signal. The conclusion of the paper is reported in Section 5.

II. LIFTING-BASED WAVELET DENOISING TECHNIQUE

A. *Lifting-Based DWT*

In wavelet transform, a signal can be analyzed at different frequency resolutions using a mother wavelet, whose characteristics should correlate to that of the original signal. DWT has the unique property of preserving both the time and frequency component in a signal and hence is a very suitable technique for the non-stationary ECG signal. The conventional DWT architecture consists of two sets of filters to perform signal decomposition namely the high-pass filter with a downsampling operation to produce the detailed coefficients (D) and the low-pass filter with a downsampling operation to produce the approximation coefficients (A). Similarly, for the inverse DWT, the detailed and approximation coefficients are upsampled and added to produce the reconstructed signal. In Fig. 1 the architectures of the forward and inverse DWT are shown where y_m refers to the input signal and $\hat{y}_m$ refers to the reconstructed signal. The standard DWT is considered inefficient because of the downsampling operation that is performed after filtering resulting in a loss of half of the output coefficients. The lifting-based DWT is termed as the second-generation wavelet-based signal processing technique which overcomes the inefficiency of the standard DWT by splitting the input signal into odd and even parts and then employs a polyphase matrix of the filter bank to produce the output coefficients. In this work, the Daubechies 2 (db 2) wavelet is used for signal decomposition because of its similarity in characteristics with the ECG signal. In [9], a complete description of the working of the lifting-based DWT using the polyphase matrix of the filter bank is given and a brief description is shown in Fig. 2. Fig. 2 shows the lifting-based DWT which consists of four steps, first is the split step which separates the input signal into its even and odd parts, the predict and the update steps which are obtained after

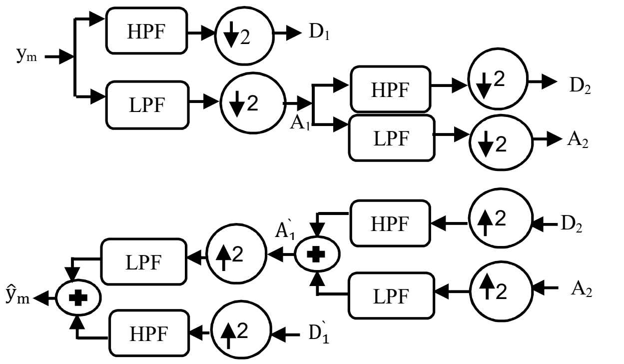


Fig. 1. Architecture of (a) Forward DWT and (b) Inverse DWT

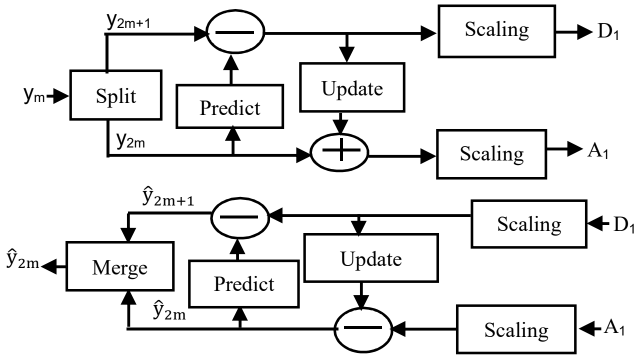


Fig. 2. Architecture of Lifting-Based (a) Forward DWT and (b) Inverse DWT

factorizing the polyphase matrix associated with the wavelet filter bank using the Euclidean algorithm, and scaling step. The db 2 forward lifting-based DWT equations to obtain the approximation and the detailed coefficients are as follows [9]:

$$D_m^1 = y_{2m+1} - \sqrt{3}y_{2m} \tag{1}$$

$$A_m^1 = y_{2m} + {\sqrt{3}}/{4}\, d_m^1 + \frac{\sqrt{3}-2}{4} d_{m+1}^1 \tag{2}$$

$$D_m^2 = D_m^1 + A_{m-1}^1 \tag{3}$$

$$A_m = \frac{\sqrt{3}+1}{\sqrt{2}} A_m^1 \tag{4}$$

$$D_m = \frac{\sqrt{3}-1}{\sqrt{2}} D_m^2 \tag{5}$$

And, the db 2 inverse lifting-based DWT equations to obtain the reconstructed signal are as follows:

$$D_m^2 = \frac{\sqrt{3}+1}{\sqrt{2}} D_m \tag{6}$$

$$A_m^1 = \frac{\sqrt{3}-1}{\sqrt{2}} A_m \tag{7}$$

$$D_m^1 = D_m^2 - A_{m-1}^1 \tag{8}$$

$$\hat{y}_{2m} = A_m^1 - {\sqrt{3}}/{4}\, d_m^1 - \frac{\sqrt{3}-2}{4} d_{m+1}^1 \tag{9}$$

$$\hat{y}_{2m+1} = D_m^1 + \sqrt{3}\hat{y}_{2m} \tag{10}$$

where D_m^1, A_m^1 and D_m^2 are the intermediate values, D_m and A_m are the obtained detailed and approximation coefficient, y_m indicates the input signal, the even and odd parts of the input signal is described as y_{2m} and y_{2m+1} respectively, $\hat{y}_m$ indicates the reconstructed output signal and *m* is the size of the input signal.

B. Wavelet-Based Denoising Technique

Wavelet-based denoising approach is based on the concept of applying thresholding to the required number of decomposition levels to suppress or remove the noise component in a signal while preserving the signal of interest. Donoho and Johnson proposed two types of thresholding techniques namely hard thresholding (HT) and soft thresholding (ST) [10]. ST is preferred over HT because in HT the signal coefficients below the threshold value are directly replaced by zero. HT leads to a loss of signal of interest, especially at the finer decomposition levels [11]. The ST is defined as [10]:

$$ST_{\lambda}(D) = \begin{Bmatrix} D-\lambda \ if\ D>\lambda \\ D+\lambda \ \ if\ D<-\lambda \\ 0 \quad\quad if\ |D| \leq \lambda \end{Bmatrix} \tag{11}$$

where λ refers to the threshold value and D are the detailed coefficients. The value of the threshold, λ for the wavelet-denoising method is calculated using the universal threshold level-dependant function. There are different ways to calculate the threshold value using various threshold functions [12]. In this paper, the universal threshold level-dependent function is considered because it is low in complexity and is directly proportional to the number of samples at a selected decomposition level. According to the universal threshold level dependant function, λ is defined as:

$$\lambda_j = \sigma_j \sqrt{2logn_j} \tag{12}$$

where *n* is the number of samples at a selected decomposition level, *j* and

$$\sigma_j = \frac{MAD}{0.6745} \tag{13}$$

where *MAD* refers to the median absolute deviation and is estimated using:

$$MAD = median(|D_j - median(D_j)|) \tag{14}$$

III. PROPOSED METHODOLOGY FOR ECG DENOISING

A. Proposed MATLAB Algorithm for ECG Noise Removal Using Lifting-Based Wavelet Denoising Technique

In this paper, the ECG data are collected from the MIT-BIH arrhythmia database (mitdb) which has a 360 Hz sampling frequency [13]. Fig. 3 shows the block diagram of the proposed lifting-based wavelet denoising technique. The noisy ECG signal is produced by adding MA and BW noise from the MIT-BIH noise stress database (nstdb) [14] with the PLI of 60 Hz sinusoidal noise. The frequency range of the ECG signal is 0.5-100 Hz, the PLI has a frequency of 60 Hz, and the MA noises have a frequency range of 10-30 Hz, so the detailed coefficients D (90-180 Hz), D_1 (45-90 Hz), D_2 (22.5-45 Hz), and D_3 (11.25-22.5 Hz), are selected to perform thresholding for the noise removal. The approximation coefficient, A_7 (0-0.7 Hz) is made zero to eliminate the BW noise with a frequency range of 0.5-0.6 Hz. The threshold values for the selected detailed coefficients are calculated using Eqs. (11-14) and ST is applied to obtain the noise-free detailed coefficients. Lastly, the inverse lifting-based DWT is performed to obtain the noise-free ECG signal.

B. Proposed VLSI Architecture of the Lifting-Based Wavelet Denoising Technique

1) Modified Lifting-Based DWT Using CSD: In section II (A), the forward and reverse lifting-based DWT equations

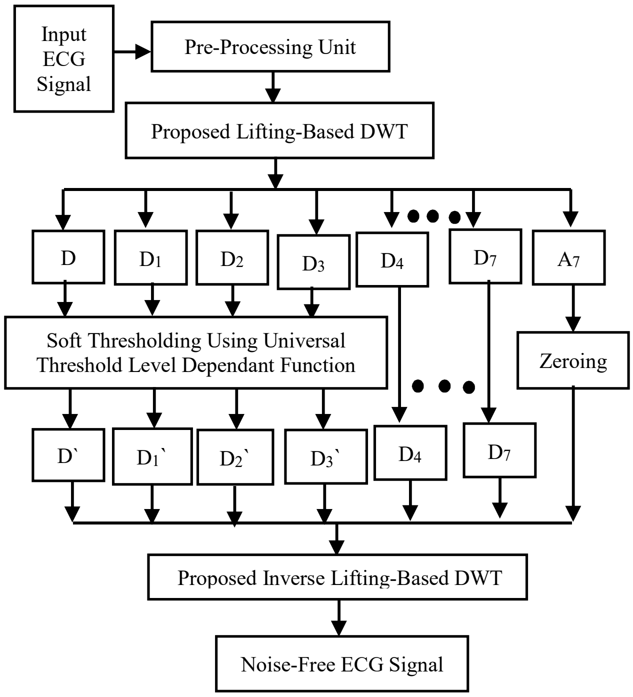


Fig. 3. Block Diagram of the Proposed Lifting-Based Wavelet-Denoising Technique

for the db 2 wavelet show that the calculation of the output wavelet coefficients and the reconstructed signal using the forward and inverse lifting-based DWT requires five steps from Eq. (1) to (5) and Eq. (6) to (11) respectively. Each step in Eqs. (1-5) and (6-10) are dependent on each other which results in a high critical path delay, so in this paper, a modified and independent one-step equation to calculate the detailed coefficients, approximation coefficients, and reconstructed signal is proposed. For the calculation of the approximation coefficients, Eq. (2) and Eq. (1) are modified and substituted in Eq. (4), which resulted in the final one-step equation for the calculation of the approximation coefficient:

$$A_m = \alpha_1 y_{2m} + \alpha_2 y_{2m+1} + \alpha_3 y_{2m+2} + \alpha_4 y_{2m+3} \tag{15}$$

For the calculation of the detailed coefficients, Eq. (3) is modified using Eq. (1) and Eq. (2) and substituted in Eq. (5). The final one-step equation for the calculation of the detailed coefficient can be expressed:

$$D_m = -\alpha_4 y_{2m-2} + \alpha_3 y_{2m-1} - \alpha_2 y_{2m} + \alpha_1 y_{2m+1} \tag{16}$$

For the reconstructed signal, Eq. (7) and Eq. (8) is modified and substituted in Eq. (9), which resulted in the one-step equation for the calculation of the even coefficients of the reconstructed signal:

$$\hat{y}_{2m} = \alpha_1 A_m - \alpha_2 D_m + \alpha_3 A_{m-1} - \alpha_4 D_{m+1} \tag{17}$$

Similarly, Eq. (8) and Eq. (9) are substituted in Eq. (10), which resulted in the one-step equation for the calculation of the odd coefficients for the reconstructed signal:

$$\hat{y}_{2m+1} = \alpha_1 D_m + \alpha_4 A_{m-1} + \alpha_2 A_m + \alpha_3 D_{m+1} \tag{18}$$

where $\alpha_1 = \frac{\sqrt{3}+1}{4\sqrt{2}}$, $\alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}$, $\alpha_3 = -\frac{-3+\sqrt{3}}{4\sqrt{2}}$, and $\alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}}$ are the modified lifting-based DWT coefficients. The modified lifting-based DWT equations for the calculation of the forward coefficients and the inverse coefficients are independent of each other and hence can work as a parallel architecture. To make the proposed modified lifting-based

DWT multiplier-less, CSD is used. The CSD approach is utilized because it offers fast multiplication by reducing the number of partial products which in turn reduces the number of addition operations. In this technique, a binary number can be expressed with the least number of non-zero digits. The conversion of a binary number into CSD representation is broadly described in [8]. In terms of 16-bit representation in fixed-point with 11 fractional bits, the modified lifting-based DWT coefficients are expressed as $\alpha_1 = 989$, $\alpha_2 = 1713$, $\alpha_3 = 459$, and $\alpha_4 = -265$. The CSD representation of the modified lifting-based DWT coefficients is as follows:

$$989 = 10000\bar{1}00\bar{1}01 = 2^{10} - 2^5 - 2^2 + 2^0 \quad (19)$$

$$1713 = 100\bar{1}0\bar{1}0\bar{1}0001 = 2^{11} - 2^8 - 2^6 - 2^4 + 2^0 \quad (20)$$

$$459 = 100\bar{1}010\bar{1}0\bar{1} = 2^9 - 2^6 + 2^4 - 2^2 - 2^0 \quad (21)$$

$$265 = 100001001 = 2^8 + 2^3 + 2^0 \quad (22)$$

where $\bar{1}$ is -1. The CSD representation also offers shift and add operations to replace the multiplication process which in turn reduces the hardware complexity significantly. The modified lifting-based DWT coefficients are expressed as shift and add operations using the CSD representation in Eq. (19-22).

2) Proposed Thresholding Block for ECG Denoising: The thresholding in the wavelet denoising technique is based on the estimation of the noise which is obtained by the MAD value as shown in Eq. (14). The MAD value is approximated using the median operation. The median operation for an array of detailed coefficients can be carried out in two steps: (1) sorting the array in the ascending order, and (2) finding the median value as the middle value in the sorted array if the number of elements in the array is odd or as the mean of the middle values if the number of elements in the array is even. The sorting of the array requires a huge number of compare operations which leads to large hardware requirements because a comparator circuit is one of the most complex circuits in the digital VLSI. To avoid the use of a comparator circuit, an optimized median calculation block is proposed in this paper. Fig. 4 shows the proposed median calculation block for the lifting-based wavelet denoising. In Fig. 4, a memory array is used which will help to sort the detailed coefficients D, D_1, D_2, and D_3 one by one. The MAD calculation in Eq. (14) involves calculating the median value twice, but the proposed MAD calculation block has been optimized with a multiplexer to perform the median calculation twice using the same architecture. For S=0, the $median(D_j)$ is calculated, and S=1, $median(|D_j - median(D_j)|)$ is calculated. Fig. 5, shows the proposed sorting algorithm using simple subtraction operations. After the sorting operation, the median calculation block in Fig. 4 calculates the median value depending on the size of the memory array. The threshold value is then calculated using Eq. (12) and (13). As can be seen from Eq. (12) and (13), the term $\sqrt{2logn_j}/0.6745$ is a constant value for each decomposition level. So, the constant terms are obtained for the selected detailed coefficients and converted into a 16-bit fixed-point representation, which was further expressed using CSD shift and add operations to avoid any multiplication in the threshold calculation. For the application of the threshold value using the ST, Fig. 6 shows an optimized ST calculation technique that does not involve any compare operations.

IV. Results and Discussions

This section describes the experiments carried out on the ECG signals to evaluate the proposed lifting-based wavelet denoising technique as well as the architecture. The proposed denoising technique to remove the BW, PLI, and MA noises is first tested in MATLAB using the ECG database, mitdb. The proposed ECG denoising technique is evaluated by calculating the following parameters:

$$Input\ SNR\ (dB) = 10log_{10}\left(\frac{\sum_{m=0}^{m-1}|y_m|^2}{\sum_{m=0}^{m-1}|(x_m - y_m)|^2}\right) \quad (23)$$

$$Output\ SNR\ (dB) = 10log_{10}\left(\frac{\sum_{m=0}^{m-1}|y_m|^2}{\sum_{m=0}^{m-1}|(\hat{y}_m - y_m)|^2}\right) \quad (24)$$

$$Improvement\ in\ SNR = (Output - Input)SNR \quad (25)$$

$$MSE = \frac{1}{m}\sum_{m=1}^{m}[(y_m - \hat{y}_m)] \quad (26)$$

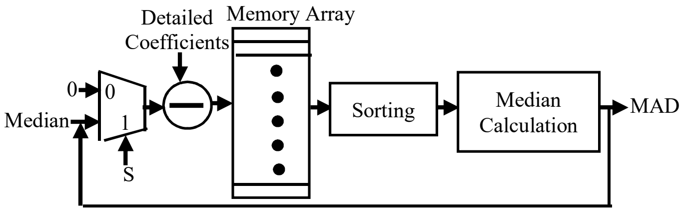


Fig. 4. Proposed Block Diagram for Median Calculation

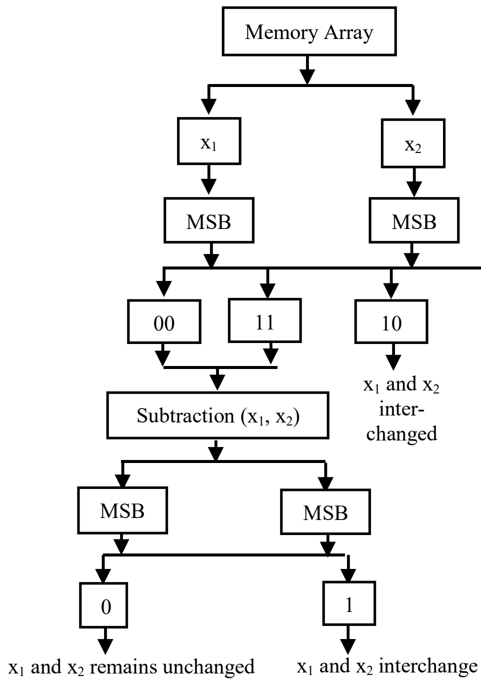


Fig. 5. Proposed Sorting Algorithm for Median Calculation

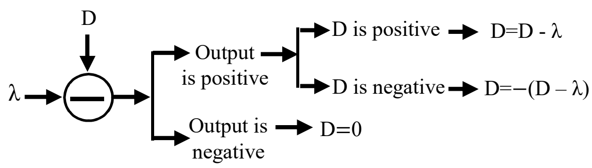


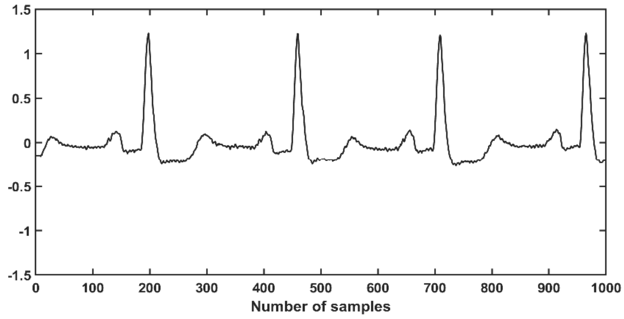
Fig. 6. Proposed Block Diagram for Soft Thresholding

where y_m, x_m, $\hat{y}_m$, m and MSE refer to the input ECG signal, ECG signal obtained after adding PLI, BW, and MA noises, denoised ECG signal, the total number of input ECG samples, and mean square error respectively.

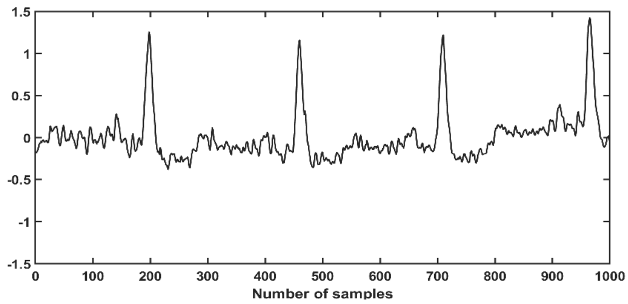
Table I shows the MATLAB results of the proposed ECG denoising technique using the mitdb. The average improvement in SNR and MSE values achieved for all 48 records from the mitdb is 7.4 dB and 0.0206 respectively. Fig. 7 shows an example of the MATLAB and FPGA results of the proposed lifting-based wavelet denoising technique on the ECG record number 105 from the mitdb. The input ECG signal is stored in the array named Input_ECG_rom, and the detailed coefficients are stored as Di where i=1:7. The threshold values for the first three decomposition levels are calculated and stored as threshold_k, where k=0,1,2 and 3. In Fig. 7 (e), the detailed coefficients D\`, $D_1$\`, D_2\`, and $D_3$\` show the noise-free detailed coefficients obtained after applying thresholding, and Output_ECG shows the noise-free ECG signal obtained after lifting-based inverse DWT. The denoised ECG signal obtained from the FPGA results is shown in Fig. 7(f). The MSE is used to calculate the difference in the output signal values between the MATLAB and FPGA results and the MSE obtained is as low as 7.08×10^{-6}. The comparison results of the proposed ECG denoising architecture with the existing ECG denoising architectures are tabulated in Table II. The proposed architecture is compared to both wavelet-packet transform and DWT using db 2 in [4]. While the operating frequency achieved is greater, the denoising architecture in [4] uses 85% more registers and 50% more LUTs than the proposed architecture. Although the CSD approach in [8] uses zero multipliers to implement DWT, the hardware utilization is still higher than the proposed architecture because, apart from CSD, the proposed architecture has been optimized by eliminating comparator and division operations, and by reducing the critical path delay. When compared to the proposed noise-removal architecture, the FPGA implementation of the delayed error normalized least mean square (DENLMS) method [15] for the removal of only white Gaussian noise uses more resources. The combined DWT and adaptive filtering method in [16] to remove ECG noises are implemented using MATLAB Simulink, and not only are more hardware resources used, but the improvement in SNR of 7.08 dB is also lower than that of the proposed technique. In comparison with the existing ECG denoising architectures, the proposed architecture outperforms in terms of resource utilization and hence is a suitable pre-processing architectural design for wearable ECG and MCT patches.

TABLE I. MATLAB RESULTS ON ECG NOISE-REMOVAL USING THE PROPOSED LIFTING-BASED WAVELET DENOISING TECHNIQUE

Record Number	Input SNR (dB)	Output SNR (dB)	Improvement in SNR (dB)	MSE
100	4.5	12	7.5	5×10^{-5}
101	5.2	10	4.8	9.2×10^{-5}
102	6	11.5	5.5	0.0024
103	4.7	14	9.3	7.6×10^{-5}
104	6	13	7	0.0018
105	6	15.2	9.2	0.0022
106	5	12.5	7.5	1.8×10^{-4}
107	6	22	16	0.0013
108	5.8	10	4.2	0.005
109	4.8	5.8	1	0.0386
111	5	12	7	0.0029
112	-2.78	6.3	9.08	0.25
113	2.2	8	5.8	0.0057
114	1.2	6.8	5.6	0.09
115	6.9	11.3	4.4	0.002
116	4	12.24	8.24	0.0034
118	1	9	8	0.01329
119	1.2	8.245	7.045	0.0019
122	6	14.5	8.5	0.0061
123	0.99	13	12.01	0.022
124	1.9	7.2	5.3	0.0101
200	1	13.5	12.5	0.0066
201	4	11	7	0.0028
208	1.4	10	8.6	0.0078
209	1	8.3	7.3	0.0044
210	3	10.2	7.2	0.0047
212	0.3	6	5.7	0.12
213	1.2	9.6	8.4	0.0074
217	2.7	12	9.3	0.0086



(a)



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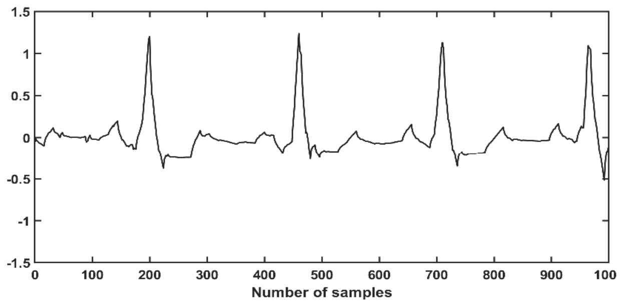

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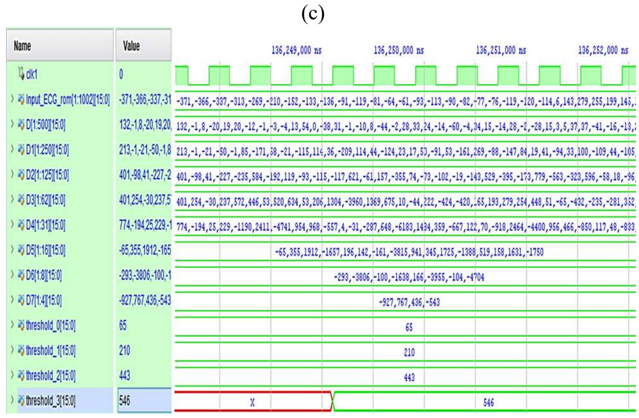
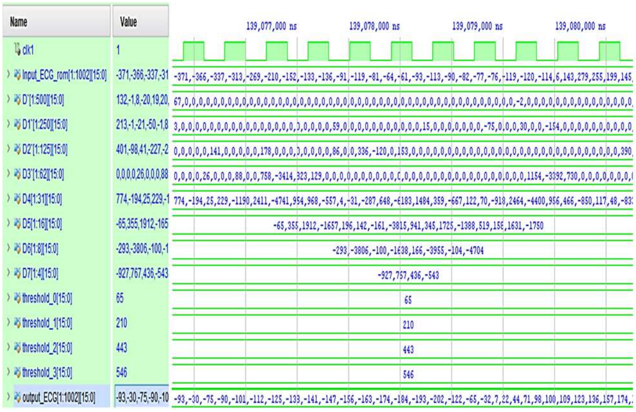
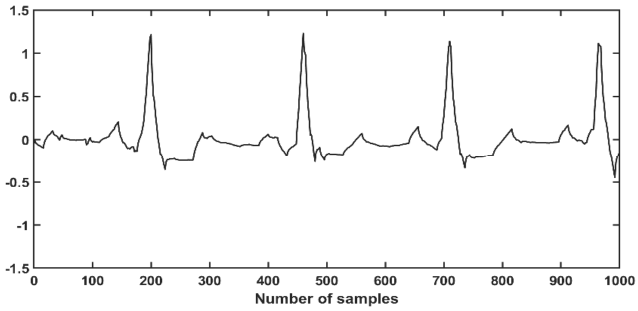

(d)



(e)



(f)

Fig. 7. (a) ECG Record Number 105, (b) Noisy ECG Signal After Adding PLI, BW, and MA Noise in MATLAB, (c) Noise-free ECG Signal Obtained in MATLAB After Applying the Proposed Denoising Technique, (d) FPGA Results Obtained for the Proposed Denoising Architecture Before Applying Thresholding to D, D_1, D_2, and D_3, (e) FPGA Results Obtained for the Proposed Denoising Architecture after Applying Thresholding to D, D_1, D_2, and D_3, and (f) Obtained Noise-Free ECG Signal from FPGA

TABLE II. COMPARISON OF THE EXISTING ECG DENOISING ARCHITECTURES WITH THE PROPOSED DENOISING ARCHITECTURES IN TERMS OF FPGA RESOURCE UTILIZATION

ECG Denoising Architecture	Slice Registers	Slice LUTs	Bonded IOBs	DSPs	Fmax (MHz)
WPT-db2 [4]	2748	7005	163	108	180
DWT-db2 [4]	3496	11335	183	132	195
CSD [8]	1227	8953	-	0	114.5
DENLMS [15]	6328	7243	120	0	-
DWT+ Adaptive Filter [16]	5919	7688	-	0	-
Proposed	389	3253	17	0	166

WPT= Wavelet Packet Transform, Fmax= Maximum Operating Frequency, DSPs= Digital Signal Processing Components, and IOBs= Input/Output Buffers

V. CONCLUSIONS

In this paper, a hardware-efficient wavelet-based ECG denoising architecture is proposed for wearable and MCT cardiac monitoring devices. The lifting-based DWT and universal level-dependent soft thresholding are used to remove the most prominent ECG noises, namely the PLI, MA, and BW. The proposed lifting-based wavelet denoising technique is tested in MATLAB using all 48 ECG data records from the mitdb, which resulted in an average SNR of 7.4 dB and MSE of 0.0206. Along with the proposed modified lifting-based DWT algorithm, the wavelet denoising blocks are also optimized to make them multiplier-less without any compare operations. In terms of FPGA implementations, the proposed wavelet denoising architecture using the modified lifting-based DWT outperforms existing ECG denoising in terms of resource utilization. The use of CSD to make the complete denoising architecture multiplier-less helped in achieving low resource utilization with a relatively high operating frequency of 166 MHz.

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