ECG Signal Compression Technique Based on Discrete Wavelet Transform and QRS-Complex Estimation

Mohammed Abo-Zahhad zahhad@yahoo.com

Electrical and Electronics Engineering Department,
Faculty of Engineering, Assiut University,
Assiut, 71515, Egypt.

Sabah Mohamed Ahmed sabahma@yahoo.com

Electrical and Electronics Engineering Department,
Faculty of Engineering, Assiut University,
Assiut, 71515, Egypt.

Ahmed Zakaria azakaria@yahoo.com

Electrical and Electronics Engineering Department,
Faculty of Engineering, Assiut University,
Assiut, 71515, Egypt.

Abstract

In this paper, an Electrocardiogram (ECG) signal is compressed based on discrete wavelet transform (DWT) and QRS-complex estimation. The ECG signal is preprocessed by normalization and mean removal. Then, an error signal is formed as the difference between the preprocessed ECG signal and the estimated QRS-complex waveform. This error signal is wavelet transformed and the resulting wavelet coefficients are threshold by setting to zero all coefficients that are smaller than certain threshold levels. The threshold levels of all subbands are calculated based on Energy Packing Efficiency (EPE) such that minimum percentage root mean square difference (PRD) and maximum compression ratio (CR) are obtained. The resulted threshold DWT coefficients are coded using the coding technique given in [1], [21]. The compression algorithm was implemented and tested upon records selected from the MIT - BIH arrhythmia database [2]. Simulation results show that the proposed algorithm leads to high CR associated with low distortion level relative to previously reported compression algorithms [1], [15] and [19]. For example, the compression of record 100 using the proposed algorithm yields to CR=25.15 associated with PRD=0.7% and PSNR=45 dB. This achieves compression rate of nearly 128 bit/sec. The main features of this compression algorithm are the high efficiency and high speed.

Keywords: ECG Signals Compression, QRS-complex estimation, Energy Packing Efficiency, Discrete Wavelet Transform.

1. INTRODUCTION

An ECG signal is a graphical representation produced by an electrocardiograph, which records the electrical activity of the heart over time. The ambulatory monitoring system usually requires continuous 12 or 24-hours ambulatory recording for good diagnostic quality. For example, with the sampling rate of 360 Hz, 11 bit/sample data resolution, a 24-h record requires about 43 M-Byte per channel. So, 12-channel system requires nearly 513.216 M-Byte of storage disks daily. Because of the tremendous amount of ECG data generated each year, an effective data compression schemes for ECG signals are required in many practical applications including ECG data storage or transmission over telephone line or digital telecommunication network. ECG data compression techniques are typically classified into three major categories; namely direct data compression [3]-[4], transform coding [5]-[8], and parameter extraction methods [9]-[11]. The direct data compression methods attempt to reduce redundancy in the data sequence by examining a successive number of neighboring samples. These techniques generally eliminate samples that can be implied by examining preceding and succeeding samples. Examples of this approach include amplitude zone epoch coding AZTEC [3], coordinate reduction time encoding system(CORTES), delta coding algorithms, the SLOPE and the approximate Ziv-Lempel algorithm (ALZ77) [4]. Transform coding of ECG signals is one of the most widely used compression techniques. In these techniques a linear transformation is applied to the signal and then compression via redundancy reduction is applied in the transform domain rather than in the time domain. Typically, the transformation process produces a sequence of coefficients which reduces the amount of data needed to adequately represent the original signal. Many different transformations have been employed: Karhunen–Loeve transform (KLT), Fourier transform (FT), Cosine transform (CT), Walsh transform (WT), Legendre transform (LT), the optimally warped transform and subband coding [5]-[7]. In recent years the wavelet transform (WT) [13]-[14] has received great attention. The wavelet transform techniques are based on consideration of the hierarchical relationship among subband coefficients of the pyramidal wavelet decomposition as the algorithms proposed in [15]-[17]. Finally, in parameter extraction methods, a set of parameters is extracted from the original signal which is used in the reconstruction process. The idea is to quantize a small set of extracted signal features. The methods that can be classified in this group are: peak-peaking methods [9], cycle-pool-based compression (CPBC) algorithms, neural network methods [10] and linear prediction methods [11].

In this paper a new compression technique based on wavelet transform and QRS-complex estimation is proposed. There are two motivations in this work. The first motivation is the QRS-complex estimation using the extraction of significant features of ECG waveform. The second motivation is the selection of the threshold levels in each subband such that high CR and low PRD are obtained. The significant features of ECG waveform are extracted to estimate the QRS-complex. Then, the estimated QRS-complex is subtracted from the original ECG signal. After that, the resulting error signal is wavelet transformed and the DWT coefficients are threshold based on the energy packing efficiency. Finally the significant coefficients are coded and stored or transmitted.

The structure of this paper is as follows: Section 2 is a review of the discrete wavelet transform. Section 3 presents the QRS-complex detection system. Section 4 is an overview of the energy packing efficiency principle and coefficients thresholding. Section 5 shows how the coding technique works. In section 6 the algorithm is tested on selected records from the MIT - BIH arrhythmia database and compared with other coders in the literature [1], [15] and [19]. Finally the conclusion of the paper is presented in section 7.

2. Discrete Wavelet Transform

The continuous wavelet transform (CWT) transforms a continuous signal into highly redundant signal of two continuous variables — translation and scale. The resulting transformed signal is easy to interpret and valuable for time-frequency analysis. The continuous wavelet transform of continuous function, $f(x)$ relative to real-valued wavelet, $\psi(x)$ is described by:

$$W_{\psi}(s,\tau)=\int_{-\infty}^{\infty} f(x)\psi_{s,\tau}(x)\,dx \tag{1}$$

where,

$$\psi_{s,\tau}(x)=\frac{1}{\sqrt{s}}\psi\left(\frac{x-\tau}{s}\right) \tag{2}$$

s and τ are called scale and translation parameters, respectively. $W_{\psi}(s,\tau)$ denotes the wavelet transform coefficients and ψ is the fundamental mother wavelet. If $W_{\psi}(s,\tau)$ is given, $f(x)$ can be obtained using the inverse continuous wavelet transform (ICWT) that is described by:

$$f(x)=\frac{1}{C_{\psi}}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_{\psi}(s,\tau)\frac{\psi_{s,\tau}(x)}{s^2}\,d\tau\,ds \tag{3}$$

where, $\Psi(u)$ is the Fourier transform of $\psi(x)$ and

$$C_{\psi}=\int_{-\infty}^{\infty}\frac{|\Psi(u)|^2}{|u|}\,du \tag{4}$$

The discrete wavelet transform can be written on the same form as Equation (1), which emphasizes the close relationship between CWT and DWT. The most obvious difference is that the DWT uses scale and position values based on powers of two. The values of s and τ are: $s=2^j, \tau=k*2^j$ and $(j,k)\in Z^2$ as shown in Equation (5).

$$\psi_{j,k}(x)=\frac{1}{\sqrt{s_o^j}}\psi\left(\frac{x-k\tau_o s_o^j}{s_o^j}\right) \tag{5}$$

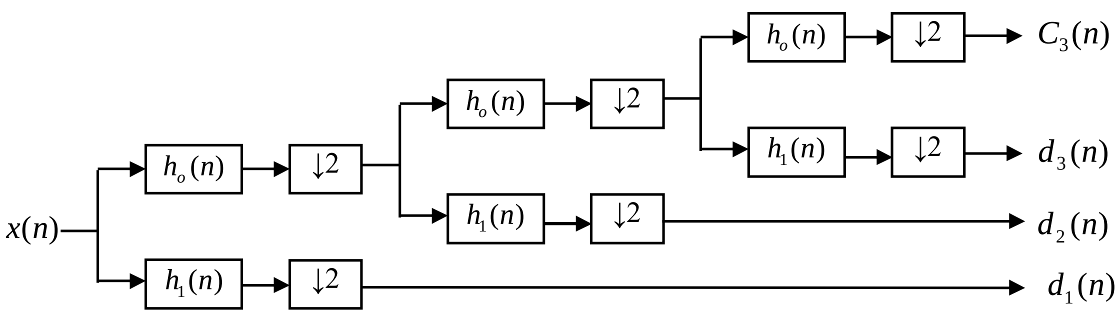
The key issues in DWT and inverse DWT are signal decomposition and reconstruction, respectively. The basic idea behind decomposition and reconstruction is low-pass and high-pass filtering with the use of down sampling and up sampling respectively. The result of wavelet decomposition is hierarchically organized decompositions. One can choose the level of decomposition j based on a desired cutoff frequency. Figure (1-a) shows an implementation of a three-level forward DWT based on a two-channel recursive filter bank, where $h_0(n)$ and $h_1(n)$ are low-pass and high-pass analysis filters, respectively, and the block ↓2 represents the down sampling operator by a factor of 2. The input signal $x(n)$ is recursively decomposed into a total of four subband signals: a coarse signal $C_3(n)$, and three detail signals, $D_3(n)$, $D_2(n)$, and $D_1(n)$, of three resolutions. Figure (1-b) shows an implementation of a three-level inverse DWT based on a two-channel recursive filter bank, where $\tilde{h}_0(n)$ and $\tilde{h}_1(n)$ are low-pass and high-pass synthesis filters, respectively, and the block ↑2 represents the up sampling operator by a factor of 2. The four subband signals $C_3(n)$, $D_3(n)$, $D_2(n)$ and $D_1(n)$, are recursively combined to reconstruct the output signal $\tilde{x}(n)$. The four finite impulse response filters satisfy the following relationships:

$$h_1(n) = (-1)^n h_0(n) \tag{6}$$

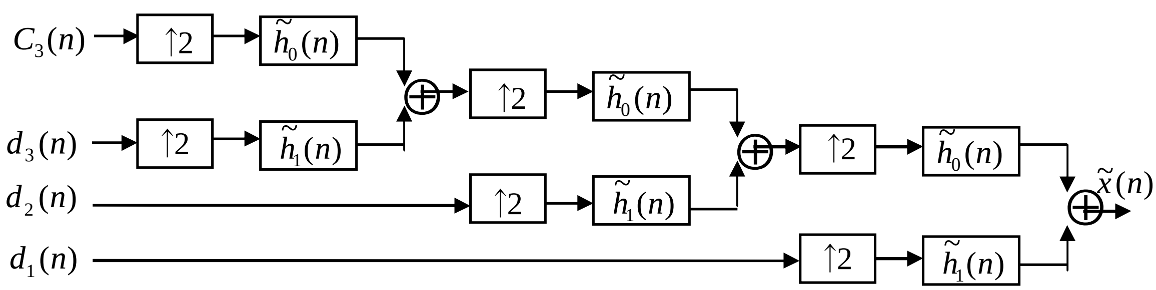
$$\tilde{h}_0(n) = h_0(1-n) \tag{7}$$

$$\tilde{h}_1(n) = (-1)^n h_0(1-n) \tag{8}$$

so that the output of the inverse DWT is identical to the input of the forward DWT.



(a)



(b)

Figure (1): A three-level two-channel iterative filter bank (a) forward DWT (b) inverse DWT

3. The QRS-Complex Detection

A typical scalar ECG heartbeat is shown in Figure (2). The significant features of the ECG waveform are the P, Q, R, S and T waves and the duration of each wave.

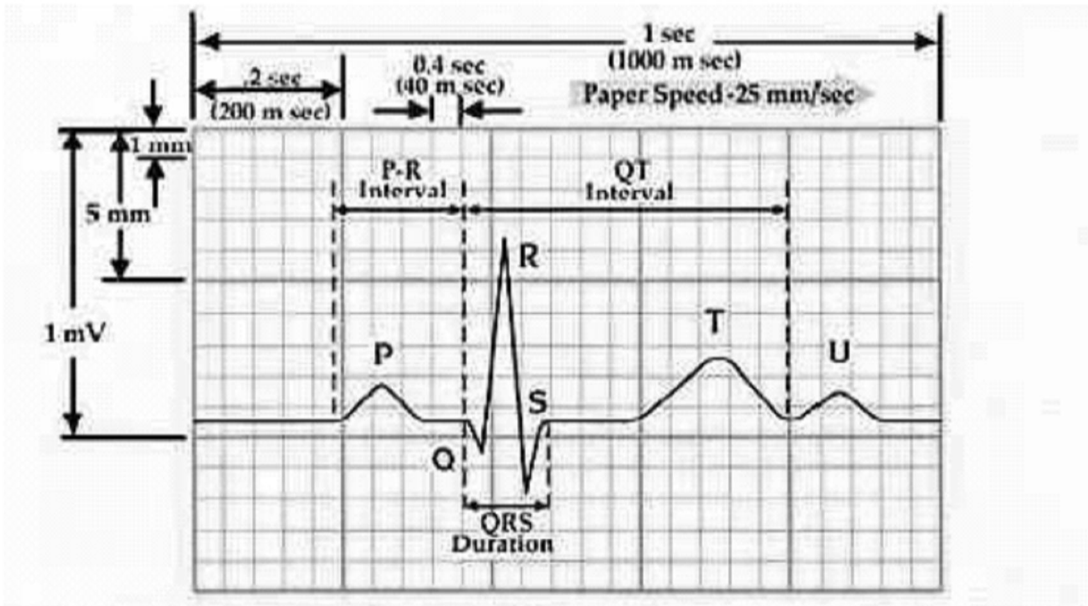


Figure (2): Typical ECG signal

A typical ECG tracing of electrocardiogram baseline voltage is known as the isoelectric line. It is measured as the portion of the tracing following the T wave and preceding the next P wave. The aim of the QRS-complex estimation is to produce the typical QRS-complex waveform using the parameters extracted from the original ECG signal. The estimation algorithm is a Mat lab based estimator and is able to produce normal QRS waveform. A single heartbeat of ECG signal is a mixture of triangular and sinusoidal wave forms. The QRS-complex wave can be represented by shifted and scaled versions of these waveforms. The ECG waveform contains, in addition to the QRS-complex, P and T waves, 60-Hz noise from power line interference, EMG signal from muscles, motion artifact from the electrode and skin interface, and possibly other interference from electro surgery equipments.

The power spectrum of the ECG signal can provide useful information about the QRS-complex estimation. Figure (3) summarizes the relative power spectra (based on the FFT) of the ECG, QRS-complex, P and T waves, motion artifact, and muscle noise taken for a set of 512 sample points that contain approximately two heartbeats [18]. It is visible that QRS-complex power spectrum involves the major part of the ECG heartbeat. Normal QRS-complex is 0.06 to 0.1 sec in duration and not every QRS-complex contains a Q wave, R wave, and S wave. By convention, any combination of these waves can be referred to as a QRS-complex. This portion can be represented by Q, R and S values, the $Q - R$ and $R - S$ durations and the event time of R as shown in Figure (2). These values can be extracted from the original ECG signal.

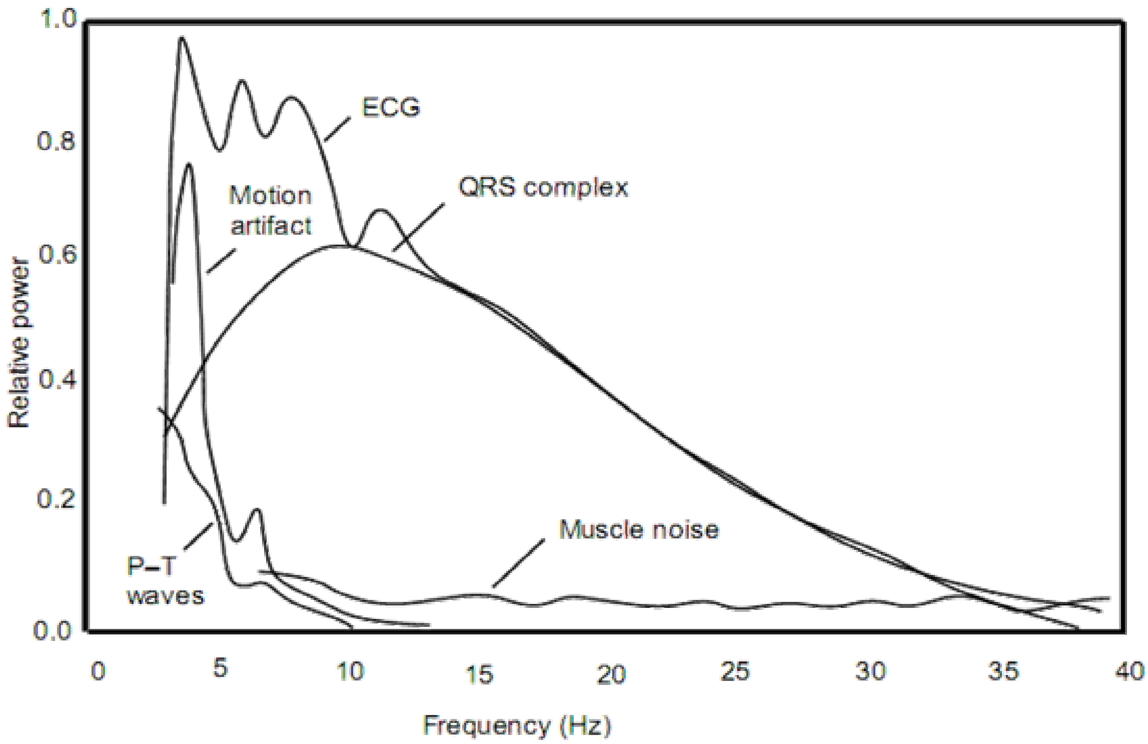


Figure (3): Relative power spectra of QRS-complex, P and T waves, muscle noise and motion artifacts.

4. Optimal Energy Packing Efficiency and Thresholding

The QRS-complex estimator is tested on the first 1000 sample of record 100 from the MIT-BIH arrhythmia database. Figure (4) illustrates the original signal, the resulting estimated QRS-complex signal and the difference between them. After applying the DWT on the error signal, the resulted wavelet coefficients are divided into the following subbands:

$$[\, A_L \quad D_L \quad D_{L-1} \quad D_{L-2} \quad \ldots\ldots\ldots \quad D_1 \,] \tag{9}$$

Where A refers to the approximation coefficients, D refer to the details coefficients and L denotes the decomposition level. To demonstrate the optimal energy packing efficiency principle, the first 4096 samples of record 103 is considered as a test signal. The percentage subband energy of all subbands of this signal are decomposed up to the sixth level using "bior4.4" wavelet filter are illustrated in Table (1). It illustrates also, the percentage energy and the number of coefficients in each subband for the original signal (S_org), the normalized signal (S_norm) and the error signal (S_diff).

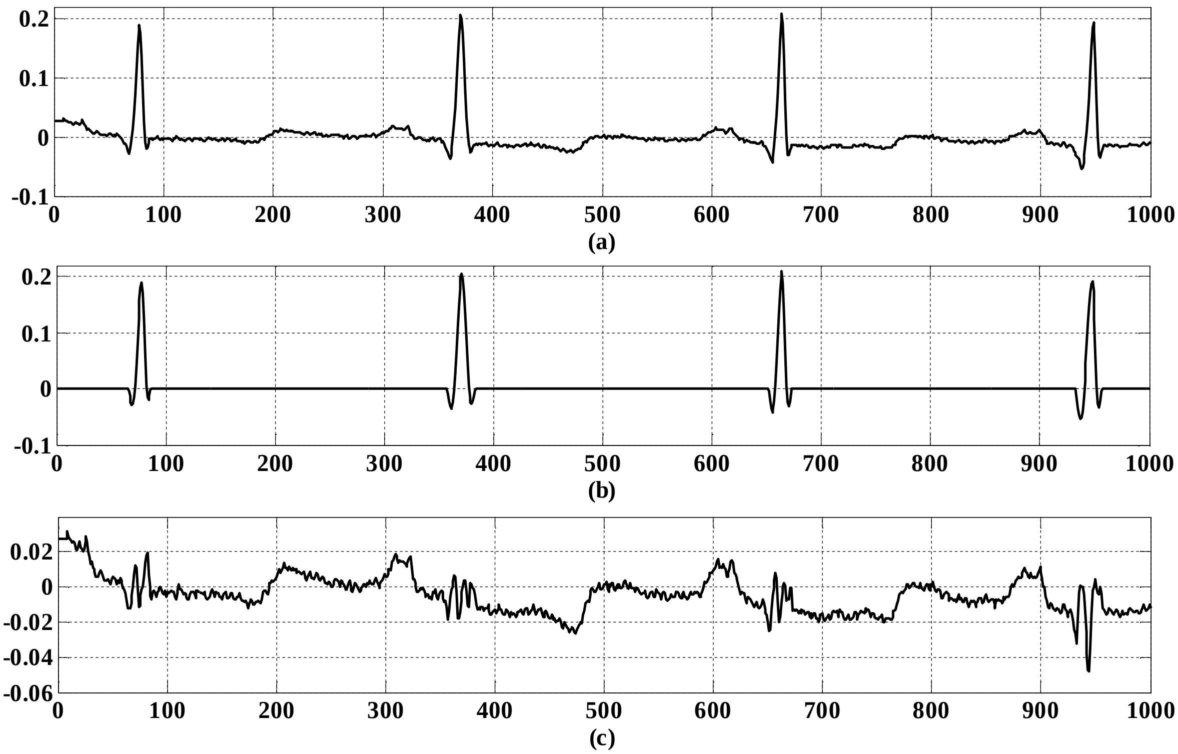


Figure (4): The first 1000 sample of record 100. a) The original signal. b) The estimated QRS -complex signal. b) Difference between the original and the estimated QRS-complex signal.

Subbands	Percentage Subband Energy			Number of coefficients in each subband
	The original signal (**S_org**)	The normalized signal (**S_norm**)	The error signal (**S_diff**)	
A_6	99.26284 %	13.80015 %	66.43408938 %	82
D_6	0.197928 %	23.14474 %	28.42895567 %	82
D_5	0.268063 %	31.34588 %	2.722341084 %	146
D_4	0.241415 %	28.22983 %	1.333762044 %	273
D_3	0.028619 %	3.346545 %	0.878562618 %	528
D_2	1.09E-03 %	0.127727 %	0.181650989 %	1038
D_1	4.38 E-05 %	0.005124 %	0.020638213 %	2057

Table (1): Record 103 percentage subbands energy, number of coefficients in each subband (S_org), the normalized signal (S_norm) and the error signal (S_diff).

Thresholding of a certain subband coefficients is done by eliminating all coefficients that are smaller than a certain threshold level L. This process introduces distortion in a certain aspect in the reconstructed signal. To decrease the effect of thresholding, threshold levels in all subbands are defined according to the energy contents of each subband. For this purpose, a percentage quantity (EPE) represents a measure of the total preserved energy of a certain subband after thresholding compared to the total energy in that subband before thresholding is defined as [21]:

$$EPE_i = \frac{\overline{E_{C_i}}}{E_{C_i}} * 100\% \tag{10}$$

where, $\overline{E}_{C_i}$ is the total energy of the coefficients in the *i*th subband after thresholding and E_{C_i} is the total energy of the coefficients in this subband before thresholding.

An optimization routine has been developed to find the threshold level of each subband that yields to the highest CR and the lowest PRD. This has been achieved through the minimization of the function P= PRD + 1/CR. However, since the value of 1/CR is small relatively to the values of PRD, a weighting factor W is introduced to increase the percentage of sharing of 1/CR. So, P is rewritten in the form:

P= PRD + W/CR (11)

The selection of W is based on which is more important: high CR or low PRD. The Mat lab optimization toolbox is adopted to perform the minimizing the objective function with threshold level T is a parameter. In a certain subband, the threshold level is calculated by carrying out the following steps for a predefined preserved energy *E'*:

1- Calculate the total energy E of the DWT coefficients C in each subband using E = $\sum_{n=1}^{M} C^2$, where *M* is the number of subband coefficients .
2- Calculate the probability distribution function f; [f, V] = hist (abs(C), 100).
3- Calculate the energy E (L) = $\sum_{i=0}^{l} V(f)^2 * f(i)$.
4- Threshold level T is the coefficient at which, l = k, where *E (k) ≤ E'*.

5. The Coding Technique

As stated in section 3, QRS-complex contains the most energy of the ECG signal. According to this observation, extracting the QRS-complex data and dealing with it in an accurate manner leads to low PRD and enhanced compression ratio. Moreover, compressing the difference between the original signal and the estimated QRS-complex one improves the overall CR. Figure (5) illustrates the block diagram of the proposed compression algorithm. The following steps detail the proposed algorithm.

A. Preprocessing

Firstly, the ECG signal $x = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad .... \quad x_N]$ is preprocessed by normalization and mean removal using the following relation:

$$y(n) = \frac{x(n)}{A_m} - m_x , \qquad n = 1,\ 2,\ ....,\ N \tag{12}$$

Where, $x(n)$ and $y(n)$ are the original and normalized signal samples respectively and *N* denotes the length of the original signal. A_m and m_x are the maximum value of the original ECG signal and the average of the normalized ECG signal respectively. The ECG signal is normalized by dividing the original signal by its maximum value A_m. Consequently, all DWT coefficients will be less than one. Mean removal is done by subtracting from the normalized ECG signal its mean m_x to reduce the number of the significant wavelet coefficients.

B. QRS-Complex Estimation.

Detecting QRS-complex and the extraction of its significant features are performed before the transformation process. The features extracted include the locations and the amplitudes of the Q, R and S peaks and their values.

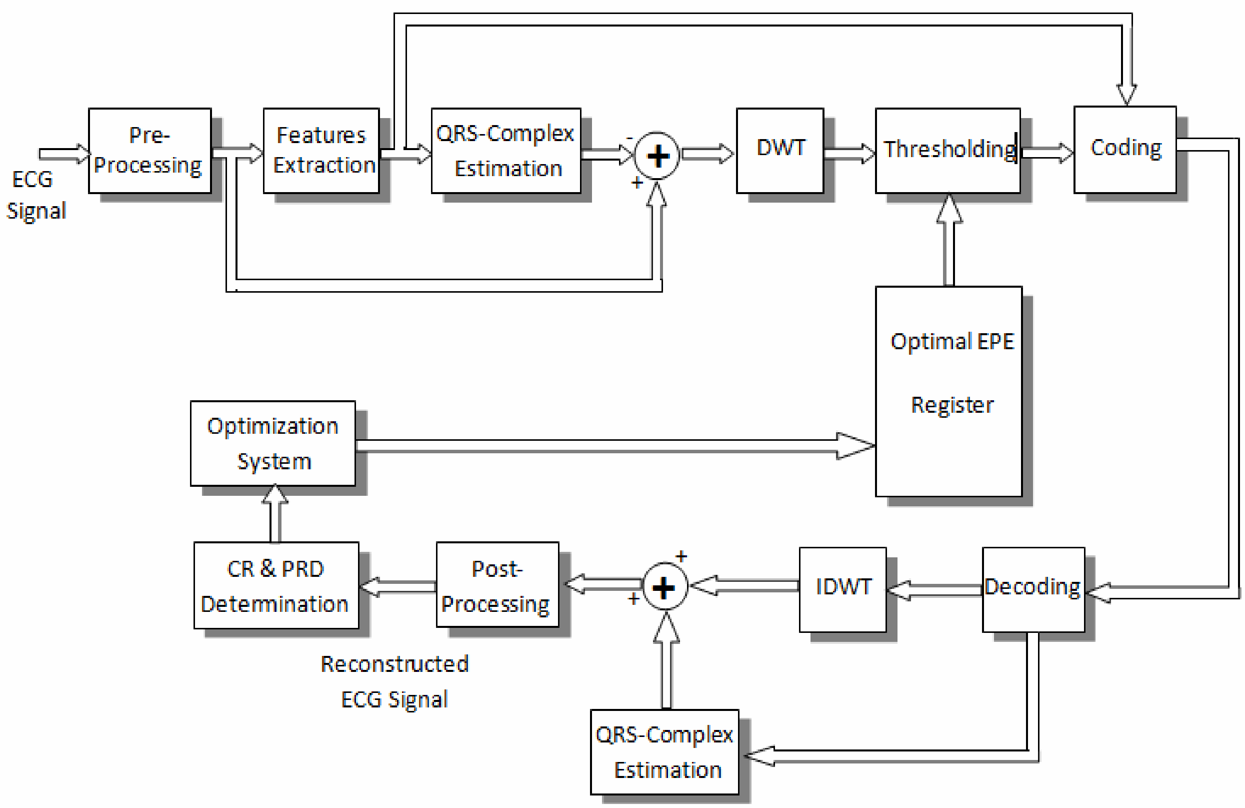


Figure (5): The block diagram of the ECG compression algorithm

C. Discrete Wavelet Transformation of the Error Signal

The error signal is discrete wavelet transformed up to decomposition level L. To obtain perfect reconstruction, the selected mother wavelet must be compactly supported. The selection of wavelet filter, decomposition level and signal length have great influence in the determination of the algorithm performance [22]-[24]. Here, the 'bior 4.4' wavelet filter is adopted.

D. Thresholding Process

The wavelet coefficients representing the error signal are threshold according to the energy packing efficiency principle explained in section 4. The intent of this part is to investigate the optimal values of EPE that achieve maximum CR and minimum PRD. To encounter this, the error signal is coded without thresholding for all subbands. Consequently, the data stream is decoded to obtain the reconstructed ECG signal. Then the CR, PRD and the objective function P are calculated. As a result the threshold level in each subband is calculated.

E. Coding of the Wavelet Coefficients

The coded stream consists of two parts:

1- The header part.
2- The significant and non significant coefficients part.

The header consists of two sections. The first section has 50 bits: 20 bits are dedicated for storing the total number of wavelet coefficients, 12 bits is dedicated for storing the maximum value in the original signal, 12 bits is dedicated for storing the mean of the normalized signal and the last 6 bits are dedicated for the number of beats contained in the signal. The second section is constructed from 66 bits: 36 bits to represent the Q, R and S values and 30 bits to represent $Q\text{-}R, R\text{-}S$ durations and the event time of R. Figures (6-a) and (6-b) illustrate the coding stream that represents the header part.

$$\bar{X}(n) = [\,y(n) + m_x\,] * A_m \qquad (13)$$

Number of coefficients	Mean Value	Maximum Value	Number of beats
20 Bits	12 Bits	12 Bits	6 Bits

(a) The first section of the header.

Q Value	R Value	S Value	Q–R duration	R–S duration	event time of R
12 Bits	12 Bits	12 Bits	10 Bits	10 Bits	10 Bits

(b) The second section of the header.

Figure (6): The coding stream of the header part.

The significant and insignificant coefficients are coded separately. The runs of significant coefficients are coded as follows:

- One bit of value *'1'* identifies the run of significant coefficients.
- A sign bit to encode the sign of the significant coefficient.
- Eight bits to encode the value of the significant coefficient.

Figure (7-a) illustrates the coding stream that represents runs of significant coefficients. The runs of insignificant coefficients are coded with variable-length coding *(VLC)* based on run length encoding as follows:

- One bit of value *'0'* identifies the run of insignificant coefficients.
- Four bits to represent the number of bits needed to code the run length.
- Variable in length code (from *1* to *16* bits) to represent the run length.

Figure (7-b) illustrates the coding stream that represents runs of insignificant coefficients.

'1'	Sign	Coefficient
1 Bit	1 Bit	8 Bits

(a) Representation of runs of significant coefficients.

'0'	Number of VLC bits	Run length
1 Bit	4 Bits	1 < VLC < 16

(b) Representation of insignificant coefficients.

Figure (7): The coding stream of the significant and insignificant coefficients.

The compression ratio CR, the percent RMS difference PRD and the peak signal to noise ratio PSNR, are used as a performance measure. The three measures are defined by:

$$CR = \frac{Length \quad of \quad x(n)*11}{length \quad of \quad output \quad stream} \tag{14}$$

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}[x(n) - \bar{x}(n)]^2}{\sum_{n=1}^{N}[x(n)^2]}} \tag{15}$$

$$PSNR = 20\log_{10}\frac{\max \quad [x(n)]}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n) - \bar{x}(n)]^2}} \tag{16}$$

where, $x(n)$ and $\bar{x}(n)$ represent the original and the reconstructed signals respectively.

F. Post Processing

The reconstructed ECG signal is obtained from decoded signal $\bar{\text{y}}(n)$ by adding the decoded mean value and multiply it by the maximum value.

6. Experimental Results

MIT-BIH arrhythmia database has been adopted for evaluating the performance of the proposed compression technique. The ECG signals of the database were sampled at 360 Hz and each sample was represented by 11 bit/sample (total bit-rate of 3960 bit/s). Two datasets formed by taking certain records from the MIT-BIH database were used for the evaluation process. These datasets were used in the evaluation of other coders in earlier studies [1], [15] and [19]. The first dataset consists of the first 10 minutes from records 100, 101, 102, 103, 111, 115, 117, and 118. The second dataset consists of the first 1 minute from records 104, 111, 112, 115, 119, 201, 207, 208, 214 and 232. The wavelet decomposition is carried out using the 'bior4.4' filter up to the sixth level. Here, the compression ratio, percent RMS difference and peak signal to noise ratio performance measures of the proposed method are compared with other coders in the literature [1], [15] and [19].

In the first experiment, the proposed algorithm is tested on records 100 and 103 in order to explore the effect of compression on the clinical information of the ECG records. Figures (8) and (9) show the two records before and after compression together with the difference between them (error signal). The optimal EPE values for all subbands are listed in Table (2).

Record Number	Parameters	Parameters in Subbands						
		A6	D6	D5	D4	D3	D2	D1
100	Maximum Coefficient Values	0.2347	0.0510	0.0323	0.0694	0.0484	0.0174	0.0058
	Optimal Threshold Levels	0.0190	0.0244	0.0159	0.0207	0.0305	0.0174	0.0058
	EPE at Optimal Threshold Levels	99.70	86.47	81.32	69.12	59.94	1.999	0.2612
103	Maximum Coefficient Values	0.2527	0.1603	0.0619	0.0660	0.0433	0.0166	0.0054
	Optimal Threshold Levels	0.0238	0.0201	0.0240	0.0246	0.0258	0.0166	0.0054
	EPE at Optimal Threshold Levels	99.92	99.58	91.12	62.86	63.24	2.228	0.868

Table (2): Maximum coefficient values, optimal threshold levels and EPE values of records 100 and 103.

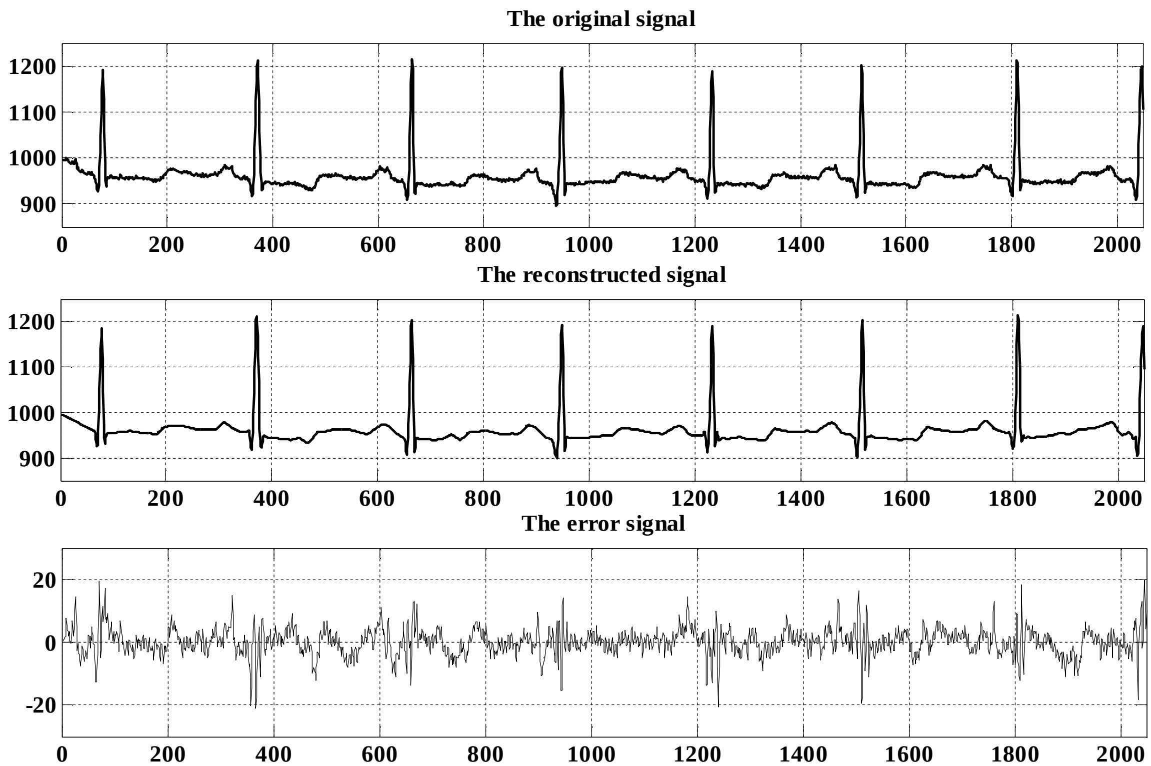


Figure (8): The original, reconstructed and error signals of the first 4096 samples of record 100 (CR= 15.4, PRD= 0.43 and PSNR= 49.4).

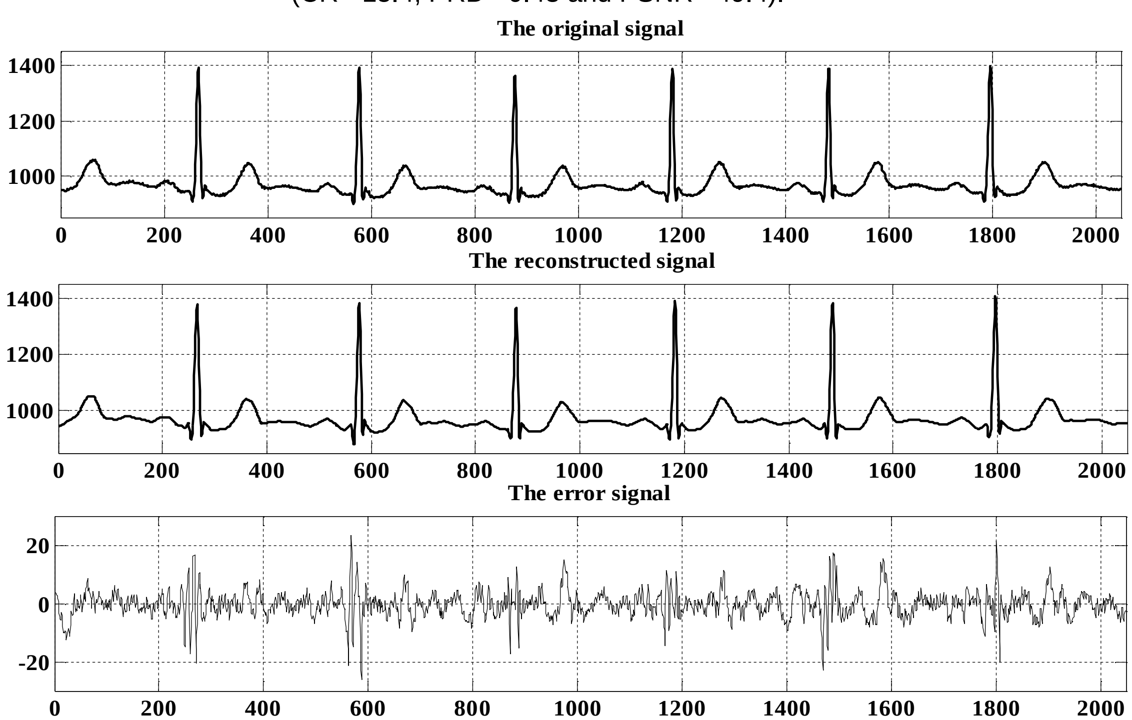


Figure (9): The original, reconstructed and error signal the first 4096 sample of Record 103 Record 103 (CR= 14.2, PRD= 0.474 and PSNR= 49.6).

To test the quality of the reconstructed ECG signals, a Mean Opinion Score (MOS) test was adopted on the reconstructed signals [20]. In this test both the original and reconstructed ECG signals of a certain record are printed in a paper form and the cardiologists evaluators are asked to see the signals. For every tested signal, the evaluators were asked to answer some questions about the similarity between the printed signals. These questions are listed in Table 3. The percentage MOS error for any tester k is given by:

$$MOS_k = factor \times \frac{5 - C}{5} \times 100 + (1 - factor) \times (1 - D) \times 100 \quad (17)$$

where,

C is a five scale that measures the similarity between the original signal and the reconstructed one (1 for completely different signals and 5 for identical signals).

D is the answer to the Boolean question about the diagnosis (0—YES, 1—NO).

and factor is a weighting coefficient between the measure of similarity and the Boolean question (0 to less than 1).

Comparison of ECG signal N0. (-----) with its original signal

1- Details of tester

Name: __________________ Date: ___________________

2- The measure of similarity between the original and reconstructed one (circle one number).

1	2	3	4	5
Completely different				**Identical**

3- Would you give a different diagnosis with the tested signal if you hadn’t seen the original signal? (circle YES or NO).

YES	NO

4- Comments:

____

____

Table (3): MOS Test Questionnaire

The mean percentage MOS error is determined as follows:

$$MOS\% = \frac{\sum_{k=1}^{N_V} MOS_k}{N_V} \times 100 \quad (18)$$

where, N_V is the number of evaluators. The lower the value of the MOS error, the evaluation quality of the reconstructed signal is better. A rough classification of signal quality to be good if the percentage MOS error is less than 35 % [20]. The ECG signal of record 100 are printed at many CR and PRD and brought forward to the evaluator cardiologists, then the percentage MOS is calculated using equation (18). Table (4) lists the resulted MOS error of all testers for Record 100 compressed at different values of CR and PRD. It is clear form the table that the MOS error values is less than 35%, which mean that all tested signals are acceptable from the point view of the cardiologists' evaluators and there are no loss in the clinical information of the ECG signal.

CR	PRD	PSNR	MOS_k %			MOS %
			1'st evaluator	2'nd evaluator	3'rd evaluator	
3.4683	0.2069	55.8949	0	0	0	0
7.4032	0.2374	54.6985	0	0	0	0
10.0654	0.2948	52.8183	0	0	0	0
14.2823	0.4429	49.2838	0	0	0	0
17.7061	0.5297	47.7294	0	0	0	0
19.2492	0.6042	46.5855	4	4	2	3.33
22.7517	0.6637	45.7702	4	6	2	4
24.2497	0.7074	45.2159	4	6	2	4
24.8425	0.7451	44.7653	4	6	2	4
27.2626	0.802	44.1255	4	6	2	4
28.2247	0.837	43.7551	4	6	4	4.66
31.4125	0.8603	43.5165	6	6	4	5.33
31.1017	0.8753	43.3662	6	6	4	5.33
32.0227	0.8859	43.2611	6	6	4	5.33
30.2728	0.8707	43.4121	6	6	4	5.33

Table (4): The MOS error of the three evaluators for Record 100.

The second experiment discusses the effect of the weighting factor *W* on the performance measures (CR, PRD, and PSNR) of the compression algorithm. The experiment is executed upon the first 4096 of record 100 while, the weighting factor *W* varies from 0 up to 100. Figure (10) shows the CR, PRD, and PSNR at the optimal vales of threshold levels versus the weighting factor *W*. It is cleared from the results of this experiment that the CR gets rise versus the increase in the weighting factor *W*. The performance results of this experiment versus the total percentage EPE of the thresholded coefficients is shown in Figure (11). Relying on the results shown in Figure (10), when *W* = 0 only PRD affect the optimization parameter P which results in CR = 3.406, PRD = 0.202 and PSNR = 55.9. On the other hand, when W = 100, only CR affect the optimization parameter P, which results in CR = 36.3, PRD = 0.99 and PSNR = 42.11. It is cleared from the obtained results that the CR and PRD increase with the increase in the weighting factor W, while PSNR decreases with the increase in W.

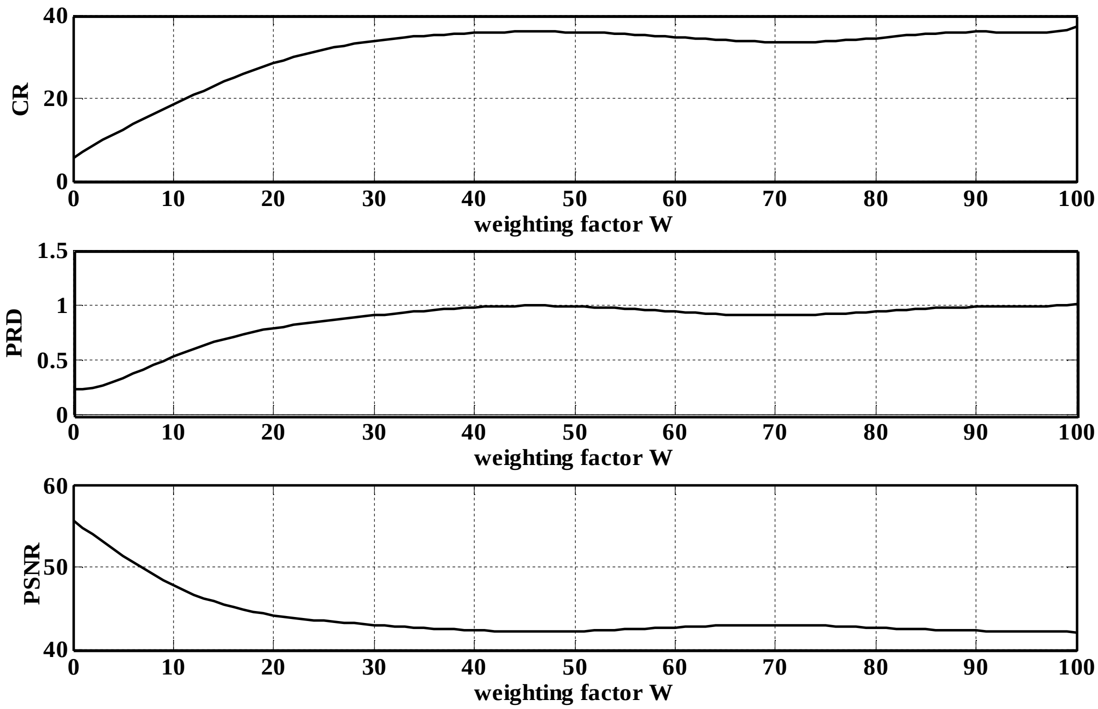


Figure (10): The CR, PRD and PSNR results versus the weighting factor W for Record 100.

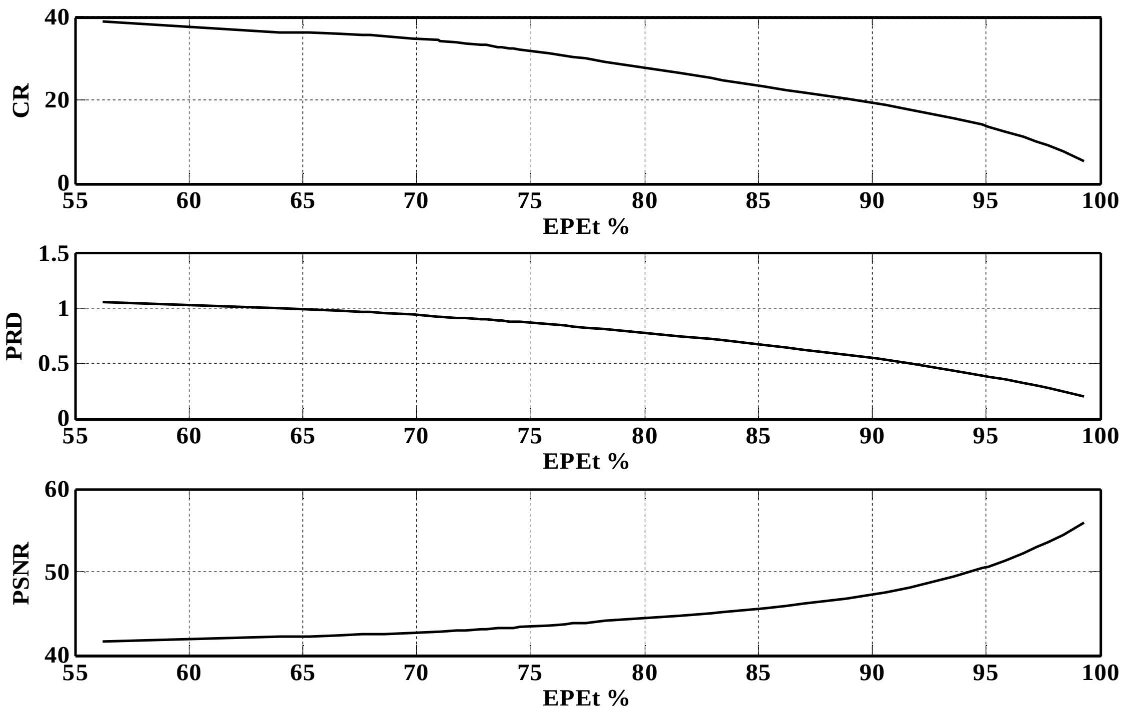


Figure (11): The performance results of record 100 versus the total EPE %.

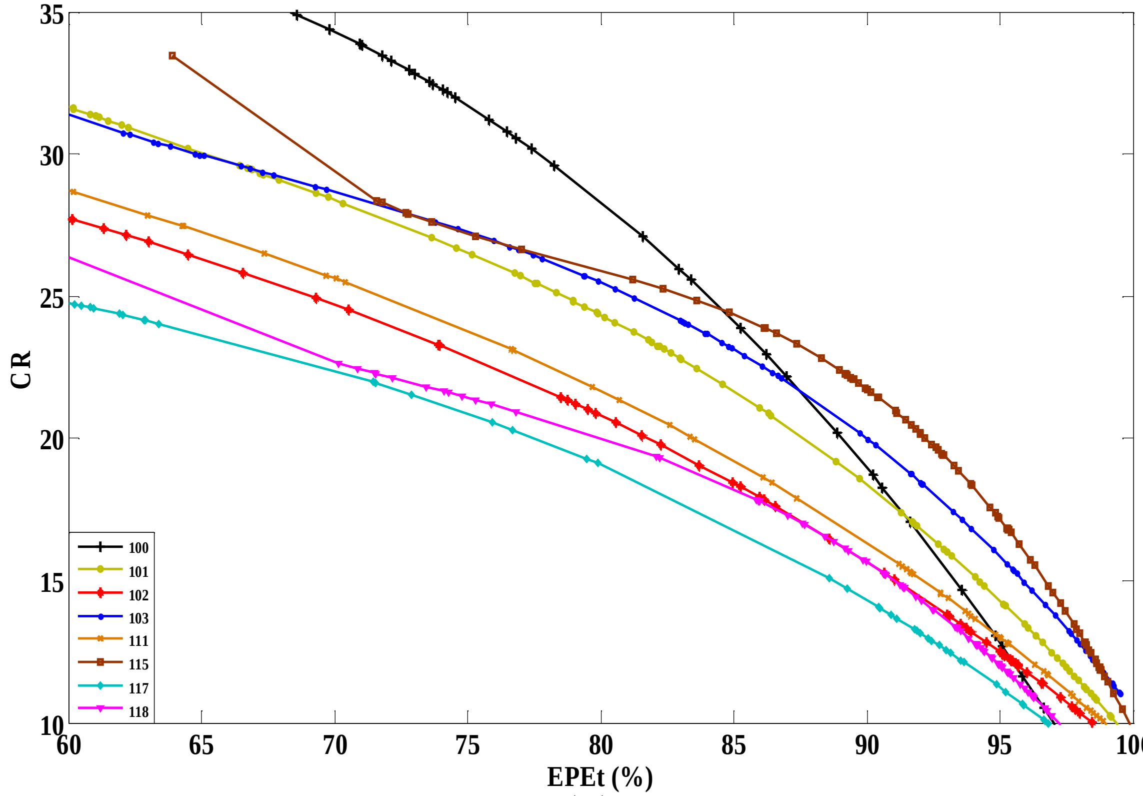
The third experiment studies the performance of the proposed algorithm in compressing the first and second data sets. Figure (12 a, b and c) and Figure (13 a, b and c) show the results of this experiment. The results indicate that, the performance results are dependant on the compressed ECG signal. For the first data set the highest CR achieved is for record 101, and the performance measure are CR = 40, PRD = 2.7% and PSNR = 32.5 dB. On the other hand, the smallest PRD achieved is for record 100, and the performance measures are CR = 3.4, PRD = 0.2% and PSNR = 55 dB. For the second data set the highest CR achieved is for record 232, and the performance measures are CR = 40.5, PRD = 1.5% and PSNR = 37.5 dB. On the other hand, the smallest PRD achieved is for record 232, and the performance measures are CR = 2.5, PRD = 0.2% and PSNR = 53 dB.

7. Conclusion

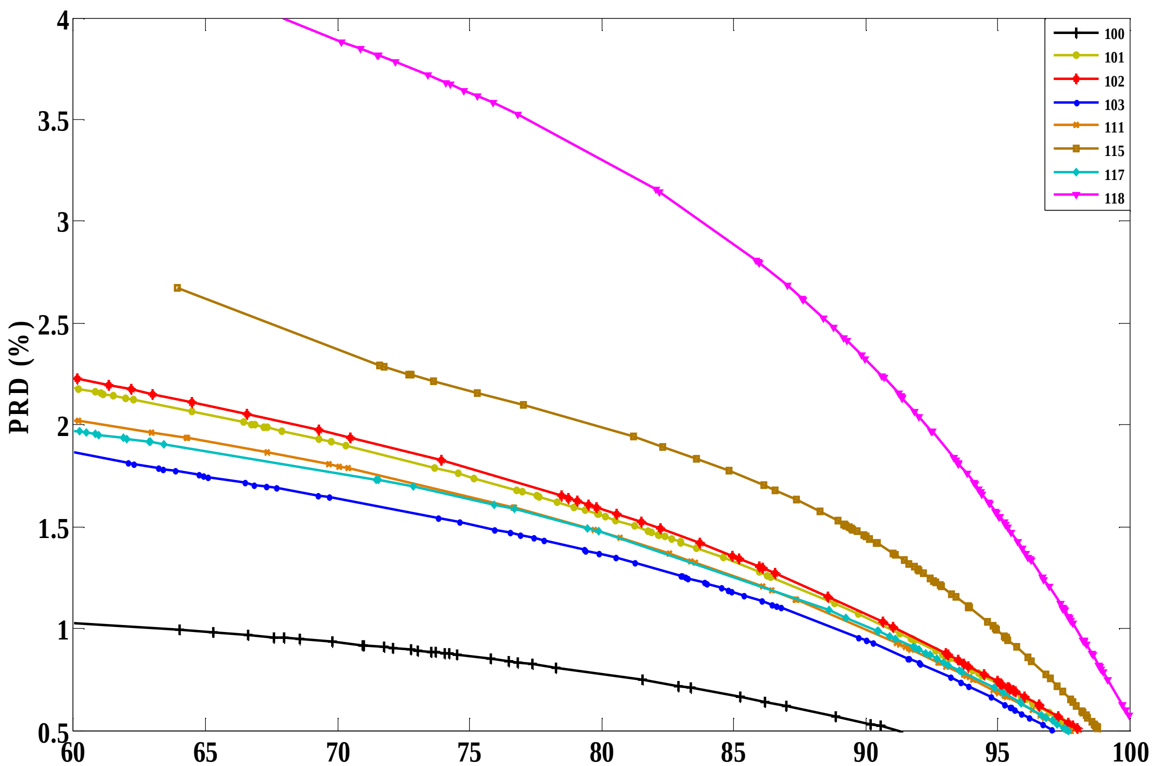
In this paper, a new method for compressing ECG signal based on wavelet transform has been proposed. The key idea lies in the estimation of QRS-complex signal from a given ECG signal. The QRS-complex is estimated using parameters extracted from the original ECG signal. This method is applied to many ECG records selected from the MIT-BIH arrhythmia database. It results in CR higher than previously published results [1], [15], [19] with less PRD as shown in Table (5).

Coding scheme	Record	CR	PRD
Reference [1]	117	22.19 : 1	1.06%
	117	10.80 : 1	0.48%
	232	4.314 : 1	0.30%
	210	11.55 : 1	0.44%
	119	23.0 : 1	1.95%
Reference [15]	117	8.00 : 1	1.18%
Reference [19]	101	26.64 : 1	9.14%
Proposed algorithm	119	23.00:1	1.95%
	232	4.314 : 1	0.25%
	210	11.55 : 1	0.49%
	101	26.70:1	1.77%

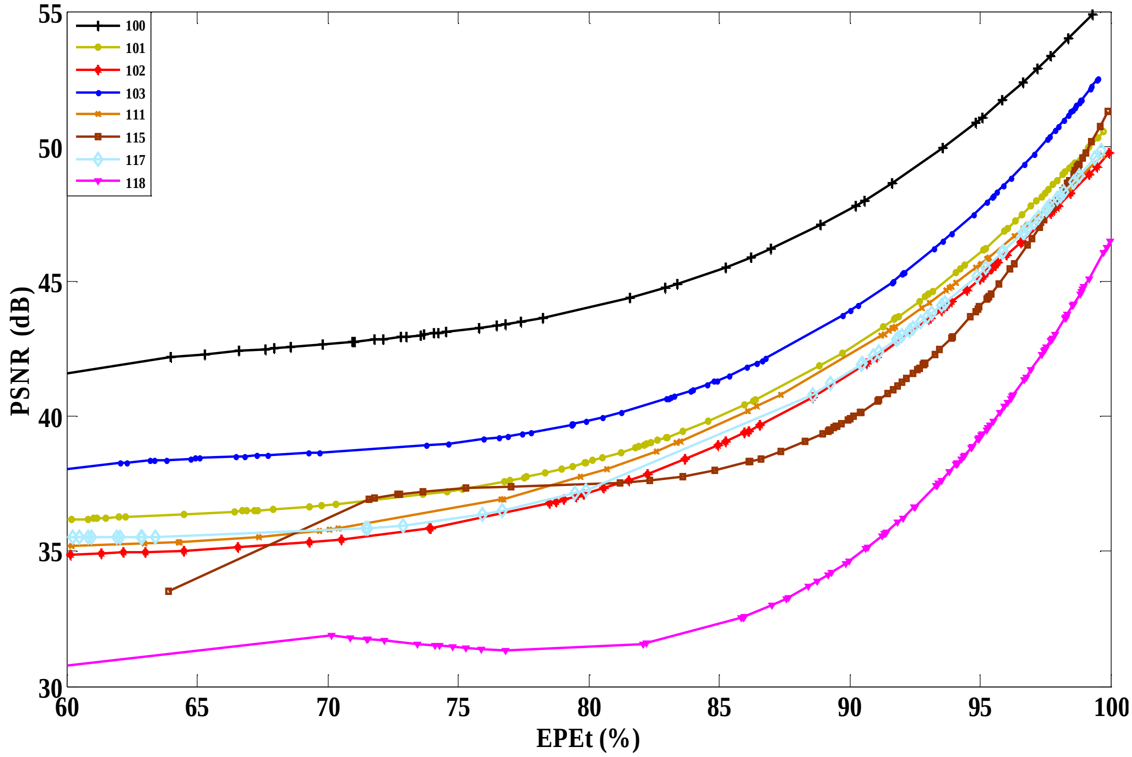
Table 5: Summary of CR and PRD results for some MIT-BIH arrhythmia database records using different algorithms versus the proposed algorithm.


35
30
25
20
15
10
CR
60
65
70
75
80
85
90
95
100
EPEt (%)
100
101
102
103
111
115
117
118

(a)

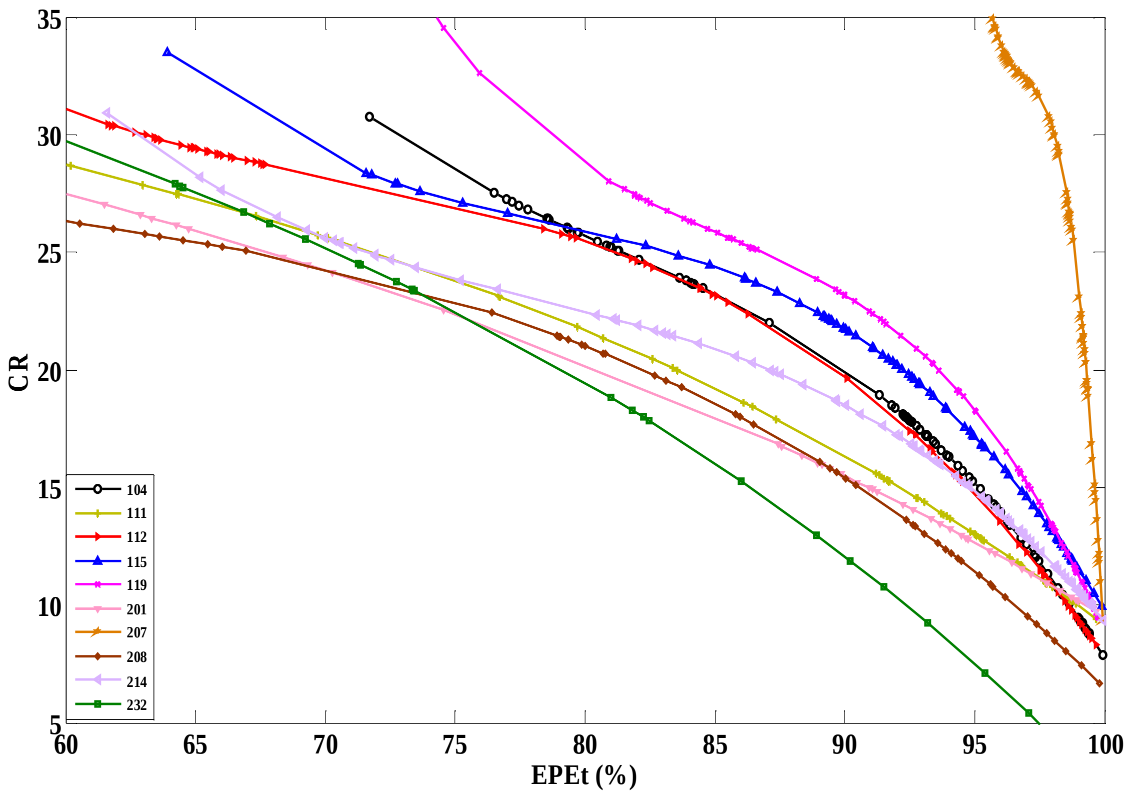

4
3.5
3
2.5
2
1.5
1
0.5
PRD (%)
60
65
70
75
80
85
90
95
100
EPEt (%)
100
101
102
103
111
115
117
118

(b)



(c)

Figure (12): The performance results for compressing the first data set.



(a)

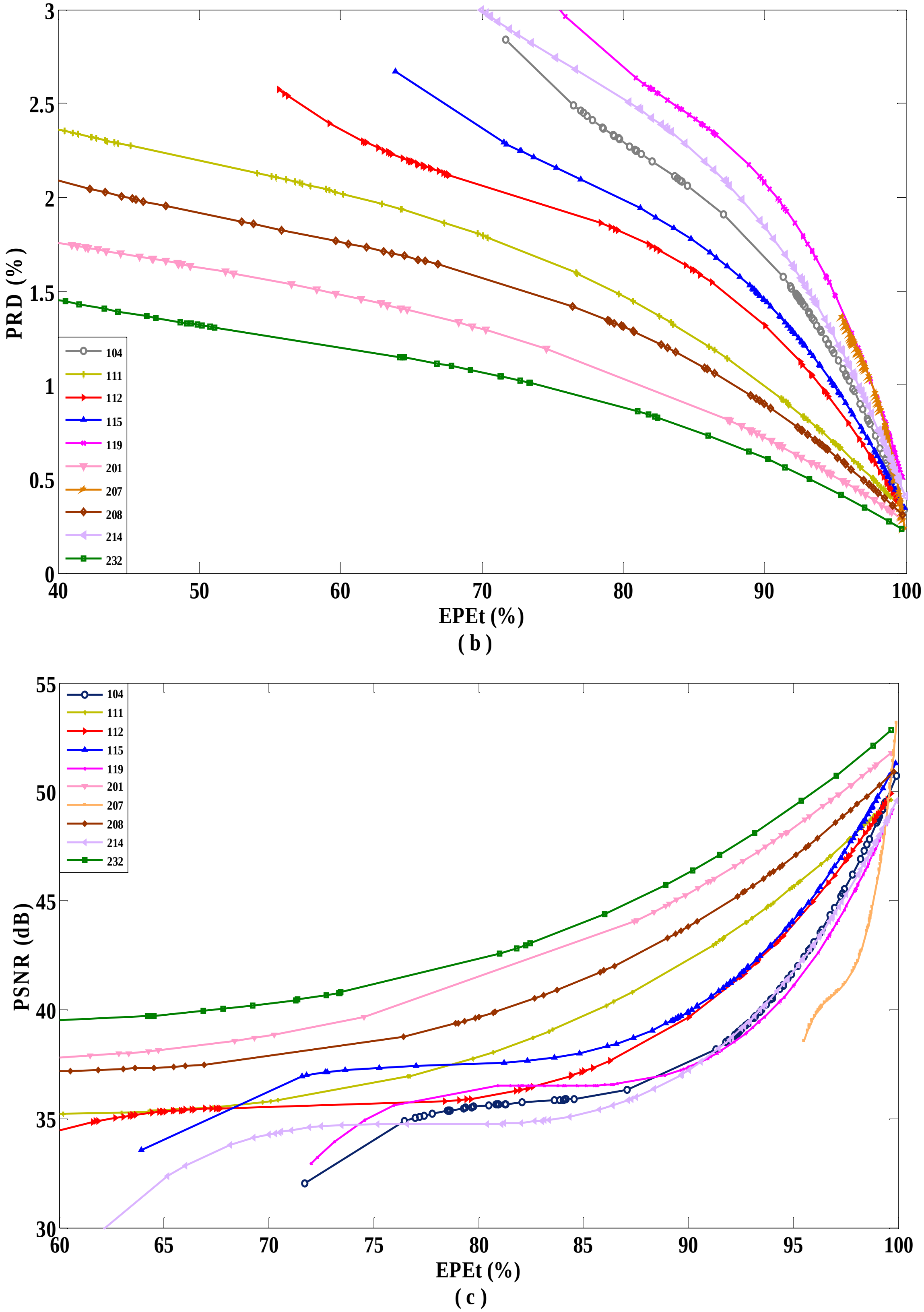


Figure (13): The performance results for compressing the second data set.

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