ECG Compression using the Three-Level Quantization and Wavelet Transform

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ABSTRACT

The Electrocardiogram signals are a very valuable source of data for physicians in diagnosing heart abnormalities. In this paper, we present an efficient technique for compression of electrocardiogram (ECG) signals. A new thresholding method based on the three level of quantization is proposed for encoding samples using an Embedded Zero-tree Wavelet (EZW) and Huffman algorithms. The modified encoding algorithm allows an optimal data compression for a target bit rate and appeared superior to other wavelet-based ECG coders. Also, to improve the efficiency of the proposed method we propose to use different types of wavelet and compare their performances for compression of the ECG signals. Experimental results show that the proposed method has a good performance and less complexity for compression of ECG database from MIT-BIH database different types of wavelet transform.

General Terms

Electrocardiogram signal, ECG, Data Compression, Thresholding, Encoding Algorithms

Keywords

Discrete Wavelet Transform (DWT), EZW, Huffman Coding, Three-Level Quantization,

1. INTRODUCTION

The electrocardiogram is commonly needed because it is a non-invasive way to establish clinical diagnosis of heart diseases. The records have become widely used to extract some considered information from the heart signals. With increasing use of ECG in heart diagnosis, such as 24 monitoring or in ambulatory monitoring systems, the volume of ECG data that should be stored or transmitted, has greatly increased. Therefore we need to reduce the data volume to decrease storage cost or make ECG signal suitable and ready for transmission through common communication channels such as phone line or mobile channel. So, an effective data compression method is needed.

The main aim of any compression method is to accomplish maximum data reduction while preserving the significant signal morphology features upon reconstruction. Compression methods can be classified into three categories: 1) direct methods: These are time-domain Techniques; where the samples of the signal are directly handled to provide the compression. Coding by time-domain methods is based on the idea of extracting a subset of significant signal samples to represent the signal. Examples of the methods belonging to this group are Amplitude-Zone-Time Epoch Coding method (AZTEC) [1], Coordinate Reduction Time Encoding System (CORTES) [2]. The key to the successful algorithm is a good rule to determine the most significant samples.

2) Linear Transformation Methods: where the original samples are subjected to a transformation and the compression is performed in the new domain. Wavelet coefficients are encoded based on the characteristics that the coefficients are ordered in hierarchies [3-5]. This implies that many of the transform coefficients will have little energy and may be discarded. A variety of encoding methods, for instance vector quantization and linear prediction, are used directly to the wavelet coefficients [6-9].

3) Parametric Methods: More recently reported in the literature, are combinations of direct and transformation techniques methods, typical examples being beat codebook [10] and artificial neural network [11]. Transform compression using the WT is an efficient and flexible scheme [12]. In recent year many of the research studies have been concentrated on Discrete Wavelet Transform (DWT) coding. Many efficient algorithms have been used to encode the DWT coefficients. Examples include: Embedded Zero-tree Wavelet encoding [13], the Set Partitioning in Hierarchical Tree (SPIHT) [14] and the wavelet coding using Vector Quantization [15].

In this paper, a different thresholding method has been performed using the Three-Level Quantization and EZW & Huffman encoding for a better compression. Figure1 shows the block diagram of the proposed method for ECG compression. For lossy compression techniques, the definition of the error criterion to appreciate the distortion information can lead to wrong diagnostics. The measurement of these distortions is a difficult problem and it is only partially solved for biomedical signals. In bio-signal compression, adopting the proper evaluation criteria is important. Most common figure used for compression performance evaluation is percentage root mean square difference (PRD), compression ratio (CR) [16-19]. In most ECG compression algorithms, the percentage root-mean-square difference (PRD) measure defined as:

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}[x(i)-\hat{x}(i)]^2}{\sum_{i=1}^{N}[x(i)]^2}} \times 100\% \qquad (1)$$

Where x is the original signal, $\hat{x}$ is the reconstructed signal, and N is the length of the window over which the PRD is calculated. In this paper the correlation coefficient (CC) is used as a measure. It is described by:

$$CC = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\overline{x})(\hat{x}_i-\overline{\hat{x}})}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\overline{x})^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i-\overline{\hat{x}})^2}} \qquad (2)$$

Where x is the original signal, $\hat{x}$ is the reconstructed signal, $\overline{x}$ is the average of original signal, $\overline{\hat{x}}$ is the average of reconstructed signal. It should be noted that this measure used to evaluate the similarity between two signals has the drawback of its global (average) nature. The compression ratio (CR) is defined as the ratio between the number of bits needed to represent the original and the compressed signal. The compression ratio is described by:

$$CR = \frac{n_{bc}}{n_{ac}} \tag{3}$$

Where n_{ac} is number of bits in the compressed signal duration and n_{bc} is number of bits in original signal.

This paper is organized as follows. Section 2 describes the discrete wavelet transform (DWT). Section 3 presents the thresholding and the three-level quantization of the coefficients vector. Section 4 explains the encoding of the quantized coefficients using EZW without thresholding and Huffman algorithms. Section 5 shows the simulation results. Section 6 concludes the paper. Here, we have proposed an algorithm using wavelet transform and EZW encoding based on the three-level quantization to achieve a better performance. As shown in Figure 1, the block diagram of the proposed method to compress ECG signals is illustrated in the following place.
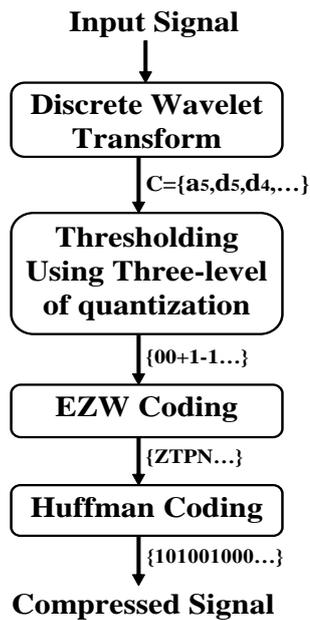
Input Signal

Discrete Wavelet Transform

$C=\{a_5,d_5,d_4,...\}$

Thresholding Using Three-level of quantization

$\{00+1-1...\}$

EZW Coding

$\{ZTPN...\}$

Huffman Coding

$\{101001000...\}$

Compressed Signal

Figure 1. Block diagram of the proposed ECG compression method

2. DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is introduced as a novel method to analyze signals in both time and frequency domains, and therefore it is suitable for the analysis of time-varying non stationary signals such as ECG. The WT overcomes the fixed resolution analysis of the short time Fourier transform (STFT). This makes the wavelets an ideal tool for analyzing signals of a non-stationary nature. Their irregular shape lends them to analyzing signals with discontinuities or sharp changes, while their compactly supported nature enables temporal localization of signals' features. A mother wavelet $\psi(t)$ is a function of zero average:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{4}$$

In discrete wavelet transform, two functions are used: wavelet function $\psi(t)$ and scaling function $\varphi(t)$. If we have a scaling function $\varphi(t)$, then the sequence of subspaces spanned by its scaling and translations:

$$\varphi_{j,k}(t) = 2^{j/2} \varphi(2^j t - k) \tag{5-1}$$

$$\varphi(t) = \sqrt{2}\sum_n h(n)\varphi(2t - n) \tag{5-2}$$

For mother wavelet we have:

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \tag{6-1}$$

$$\psi_{j,k}(t) = \sqrt{2}\sum_n g(n)\varphi(2t - n) \tag{6-2}$$

For orthogonal basis we have:

$$g(n) = (-1)^n h(-n + 1) \tag{7}$$

Where $h(n)$ is low pass filter and $g(n)$ is high pass filter. If we want to find the projection of a function $f(t)$ on this set of subspaces, it must be expressed in each subspace as a liner combination of expansion function of that subspace [20]:

$$f(t) = \sum_{k=-\infty}^{\infty} c(k)\varphi_k(k) + \sum_{j=0}^{\infty}\sum_{k=-\infty}^{\infty} d(j,k)\psi_{j,k}(t) \tag{8}$$

$\psi(t)$ is function of the discrete wavelet, the transform can be represented, as a tree of low a high pass filter, with each step transforming the output of the low pass filter. Figure2 shows the wavelet decomposition tree, where the boxes represent linear convolution and circles represent down sampling by a factor of two (removal of every other sample). The original signal is successively decomposed into components of lower resolution, while the high frequency components are not analyzed any further. At each of the DWT algorithm, there are outputs: the scaling coefficients, c_n^{j+1} and the wavelet coefficients, d_n^{j+1} .These coefficients are given respectively, by:

$$c^{j+1}(m) = \sum_{i=1}^{2m} h(2m - i)c^j(m) \tag{9}$$

$$d^{j+1}(m) = \sum_{i=1}^{2m} g(2m - i)c^j(m) \tag{10}$$

Here, g and h represent the low pass and high pass filters' transfer functions respectively. The output scaling coefficients are considered as the input samples to the next stage in the DWT algorithm [20-21]. The wavelet coefficients are described by:

$$d_n^M (n = 0,1,2,...,\frac{L}{2^M} - 1) \tag{11-1}$$

$$d_n^{M-1} (n = 0,1,2,...,\frac{L}{2^{M-1}} - 1) \tag{11-2}$$

$$\vdots$$

$$d_n^1 (n = 0,1,2,...,\frac{L}{2} - 1) \tag{11-3}$$

L denotes the maximum number of scales that can be performed. It depends on the size of the data to be analyzed.
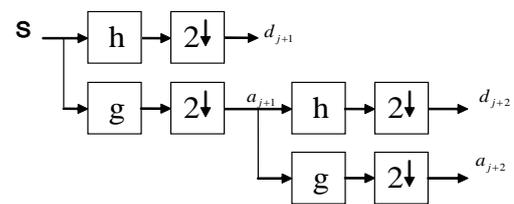

Figure 2. The Structure of Discrete Wavelet Transform

The initial decomposition produces two sets of data: a set of approximation coefficients and a set of detail coefficients. The **S** in the first row represents the entire signal, with no decomposition. The first stage represents the first level of decomposition. There, node a_{j+1} shows the approximation coefficient and d_{j+1} states the detail coefficients. This stage represents the first level of decomposition, where an approximation and detail are generated for the first level of approximation and an approximation and detail are generated for the first level detail in the second stage. In this paper, we used a discrete wavelet transform with 5 levels of

decomposition (M=5), the length of signal: 2048 samples (n=2048). All detail coefficients $\{d_5, d_4, d_3, d_2, d_1\}$ (1≤M≤5) and approximation coefficient a_5 (M=5) are assembled together in the coefficient vector (C):

$$C = [a_5, d_5, d_4, d_3, d_2, d_1]$$

2.1. Orthogonal Wavelets (dbN, symN)

Let us recall that a multiresolution approximation is a nested sequence of linear space. The orthogonal complement W_j of V_j in V_{j-1} can be thus defined:

$$V_{j-1} = V_j \oplus W_j \qquad (12)$$

Then there is a function ψ such that the family $\psi_{j,n}(t) = 2^{-j/2} \psi(2^{-j}t - n)$, n in Z, is an orthonormal basis of W_j. The family $\psi_{j,n}$, j in Z and n in Z, is an orthonormal basis of L^2 and:

$$L^2(R) = V_j \oplus_{j \in Z} W_j = V_j \oplus_{k \le j} W_k \qquad (13)$$

ψ is an orthogonal wavelet associated to the multi-resolution approximation [27]. A signal f in L^2 can be decomposed as:

$$f(t) = \sum_{j,n \in Z} < f, \psi_{j,n} > \psi_{j,n}(t)$$

$$= \sum_{n \in Z} < j, \varphi_{j,n} > \varphi_{j,n}(t) + \sum_{k \le j, n \in Z} < f, \psi_{k,n} > \psi_{k,n}(t) \qquad (14)$$

φ is an orthogonal scaling function of the multiresoution. One can verify the other resolutions are generated by a suitable dilatation of these bases of translated atoms. Since the resolutions are embedded, there is necessarily a sequence of real number $h[n]$ such that:

$$\frac{1}{\sqrt{2}} \varphi(\frac{t}{2}) = \sum_{n=-\infty}^{+\infty} h[n] \varphi(t - n) \qquad (15)$$

In this study, we have examined the symN and dbN wavelet families that include: Sym8, Sym7, Sym5, db3 and db2.

2.2. Biorthogonal Wavelet (BiorN)

Leave Biorthogonal wavelets are defined similarly to orthogonal wavelets, except that the starting point is biorthogonal multi-resolution approximations. The following decompositions are performed:

$$V_{j-1} = V_j \oplus W_j \, with \, W_j \subset (V_j^+)^\perp \qquad (16-1)$$

$$V_{j-1}^+ = V_j^+ \oplus W_j^+ \, with \, W_j^+ \subset (V_j)^\perp \qquad (16-2)$$

Like in the orthogonal case, a signal in L can be written as:

$$f(t) = \sum_{j,n \in Z} < f, \psi_{j,n}^* > \psi_{j,n}(t) =$$

$$= \sum_{n \in Z} < j, \varphi_{j,n}^* > \varphi_{j,n}(t) + \sum_{k \le j, n \in Z} < f, \psi_{k,n}^* > \psi_{k,n}(t)$$

$$= \sum_{j,n \in Z} < f, \psi_{j,n} > \psi_{j,n}^*(t) \qquad (17)$$

$$= \sum_{n \in Z} < j, \varphi_{j,n} > \varphi_{j,n}^*(t) + \sum_{k \le j, n \in Z} < f, \psi_{k,n} > \psi_{k,n}^*(t)$$

In this paper, we have tested the Bior wavelet families that include: Bior4.4, Bior3.3, Bior3.1 and Bior2.2 as the biorthogonal wavelets.

3. THREE-LEVEL QUANTIZATION

In this section, the quantization of the coefficient vector (C) is described. Due to the quantization, perfect reconstruction is not possible, and reconstruction errors occur. The quantization is performed iteratively by a three-level quantizer. Given the input

vector C and the threshold Θ_i of the ith iteration, Θ_i described by:

$$\Theta_i = \begin{cases} \frac{1}{2}.\max_k(|c[k]|),.....(i=1) \\ \frac{1}{2}.\Theta_{i-1},.................(i>1) \end{cases} \qquad (18)$$

$$\forall k \in 1,2,...,N$$

Where Θ_i is a threshold of the ith iteration that is generated by the above equation for beginning of quantization. The coefficients of vector (C) are quantized by the quantizer that is defined by equation (19). The quantized coefficients $d_{\Theta_n}[k]$ are described by:

$$d_{\Theta_i}[k] = \begin{cases} 1, & if\,(c[k] - \sum_{n=1}^{i=1} d_{\Theta_i}[k].\Theta_i) > \Theta_i \\ -1, & if\,(c[k] - \sum_{n=1}^{i=1} d_{\Theta_i}[k].\Theta_i) < -\Theta_i \\ 0, & else \end{cases} \qquad (19)$$

$$\forall k \in 1,2,...,N$$

In this stage, the input vector includes a set of approximation and detail coefficients that is created in the five levels of decomposition. Results of this step are the quantized coefficients vector (C) that is generated by the equation (19). The quantized coefficients that are named $d_{\Theta_n}[k]$ include exclusively three symbols {-1, 0, 1}. Where $d_{\Theta_n}[k]=0$ denotes the insignificant coefficients that is not very important for reconstruction of the original signals and $d_{\Theta_n}[k]=\pm 1$ the significant ones that are very effective to decrease error rate. The wavelet coefficient $\hat{c}[k]$ can be reconstructed by using the quantized coefficients and the initial threshold Θ_1:

$$\hat{c}[k] = \Theta_1 \sum_{n=1}^{i} d_{\Theta_n}[k].2^{n-1} \qquad (20)$$

4. EZW AND HUFFMAN ENCODING

The EZW algorithm has two very interesting properties [22-23-24]. The first is that the EZW algorithm creates a connection between the wavelet coefficients from different sub-bands. This is the reason why several quantized coefficients from different sub-bands can be encoded using only one symbol .The second property is that the import coefficients are encoded using the successive approximated technique, which puts the most important parts of the coefficients at the beginning of a bit stream. Therefore, the encoder can easily stop encoding procedure at any desired target rate.

In this section, the encoding of the quantized coefficients is performed at each iteration level of the quantization procedure. The main goal of the encoding algorithm is to find a connection between the quantized coefficients $d_{\Theta_i}[.]$ from different sub-band. Also we don't need to calculate the threshold again by $thr = 2^{[\log|\max(C)|]}$ equation because of the thresholding of the coefficient vector (C) in the previous section. Therefore in this stage, we only need to encode the results of the previous step to receive a better performance.

The EZW algorithm use an alphabet which includes four symbols {P, N, T, Z}. Symbols P and N indicate the sign of a significant quantized coefficients, respectively for values of +1 and -1. A non-significant coefficients is encoded with the symbol {T} if it the root of a zero-tree where all of its coefficients are non-significant. A zero-tree and its members are encoded with only one symbol, namely with its root. The

symbols {Z} describes those quantized coefficient, which are zero and do not belong to a zero-tree. The results of this stage are an encoded coefficients vector C with four symbols {P, N, T, Z}.

In the next stage, these coefficients with the Variable-Length Coding (Huffman Coding) are encoded. In the Huffman encoding, a code with shorter length is replaced by symbols that have a small number and a code with longer length is substituted by symbols that their number is very large. We have considered the number of each symbol and Z, T, P and N have been replaced by 1, 01, 001 and 000 codes, respectively. Table1 describes this procedure:

TABLE 1. ENCODING SYMBOLS IN THE HUFFMAN ALGORITHM

Symbol	Code
Z	1
T	01
P	001
N	000

5. SIMULATION RESULTS

In this section, we have compared the result of several experiments of our method with other ECG coders. The proposed algorithm was tested and evaluated using actual data from MIT-BIH arrhythmia database. These ECG databases were sampled at 360 Hz with the Resolution of 11 bits/sample. We have used Daubechies (db3, db2), Symlet (sym8, sym7, sym5) and Biorthogonal wavelets (Bior2.2, Bior3.1, Bior3.3, Bior2.6, Bior4.4) with five levels of decomposition. The following results have been obtained using the records number: 101, 103, 105, 115, 117, 118, 119, 201, 205, 213 and 219. To gain an optimum performance, 2048 samples and 3 types of wavelet with 5-level decompression have been used for compression of ECG signals. In order to validate the proposed compression algorithm and to compare it with other methods, 11 records consisting of the 2048 samples from the MIT-BIH Arrhythmia database have been used. The ECG signals were digitized through sampling at 360 (samples/s), quantized and encoded with 11 bits.

We have compared the performance of our encoder with some kinds of encoders in the literature, wavelet-based coders and direct ECG signal coders. The PRD and CR results in a similar record have been compared. Now, the effects of the iterations of the three-level quantization on the PRD, CR have been evaluated.

TABLE 2. A COMPRESSION OF DIFFERENT ENCODING ALGORITHM FOR RECORD 117

Algorithms	PRD (%)	CR (%)
JPEG2000 [25]	1.03	10:1
Sec & SPIHT [26]	1.01	8:1
SPIHT & VQ [27]	1.45	8:1
SPIHT [28]	1.8	8:1
Hilton [35]	2.6	8:1
WT & Huffman [11]	3.2	9.4:1
Djohn [36]	3.9	8:1
Wavelet Neural Network [33]	2.74	7.6:1
Jianhua Chen [32]	1.08	12:1
the block-based discrete cosine transform (DCT)[34]	1.18	9.56:1
RLE [29]	2.915	5.8:1
ASCII [30]	7.89	15.72:1
Benzid [9]	3.51	12.6:1
Dc Equalization and Complexity Sorting [31]	1.118	13.75:1
Proposed Technique	**0.97**	**13.92:1**

Table 2 shows the performance of the different algorithms in comparison with our simulated results. According to the table, there are some ECG compression methods in the literature, The Wavelet Neural Network, RLE, Benzid, Jianhua Chen, Hilton, SPIHT, SPIHT&VQ, Sec&SPIHT and WT&Huffman methods have presented a wavelet and wavelet packet-based EZW encoder [7]. They have reported respectively the PRD values of 2.74%, 2.915%, 3.51, 1.08, 2.6%, 1.8%, 1.45%, 1.01% and 3.2 with CR lower than 13. Also by comparison with other coders, the PRD ranges of 1.18%, 1.03% and 3.9% in Table 2 are significantly higher (inferior) compared to our results and also, their CR values of 9.56%, 10% and 8% are noticeably lower (inferior) in comparison with our presented results. In ASCII [36] a combination of CR and PRD that has been received is so bad. In table 2, the best combination of CR and PRD values of the coder compared here which is considerably better than others is 13.75:1% and 1.118% for the Dc Equalization and Complexity Sorting method [38]. The proposed compression algorithm in this paper obtain an excellent performance (PRD=0.97% and CR=13.92:1%) that is extremely better than other coders.

Figure 3 shows the effects of the iterations of quantization on PRD. According to the Figure, as the numbers of iterations increase, the values of PRD can be improve more and in low number of iterations, the PRD values increase sharply and it would be worse than. Fig. 4 shows the effects of the iterations of quantization on CR. It can be found from the Figure 4 that the values of CR would be increased when the numbers of iteration become lower. In other words, by decreasing the numbers of iteration, the values of CR can be better and by increasing iterations, the CR values would be worse.

We show the results of the 9th, 8th, 7th, 6th and 5th iterations in Tables 3, 4, 5, 6 and 7 for eleven records. In this study, several types of wavelets named: db3, db2, Bior4.4, Bior3.3, Bior3.1, Bior2.2, Sym8, Sym7 and Sym5 are examined.
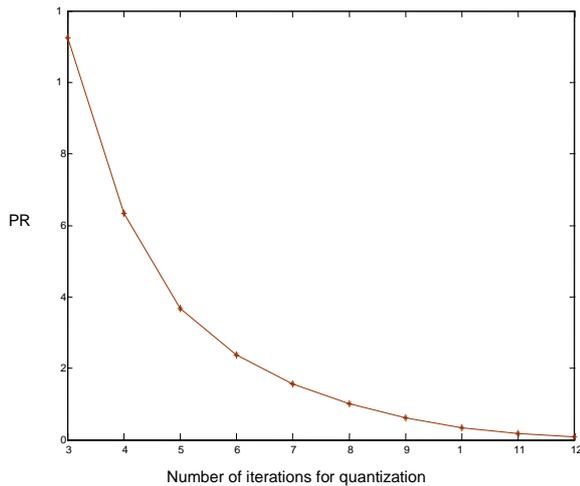
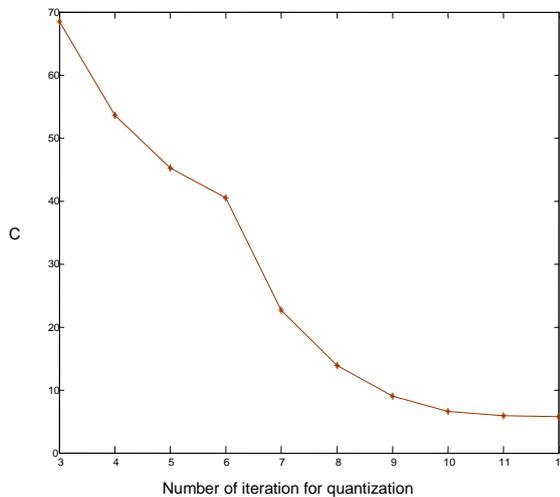**Figure 3. The effects of the iterations of quantization on PRD**

Figure 4. The effects of the iterations of quantization on CR

Table 3 shows the achieved results for compression of the 9th iteration. The highest compression ratio (CR=15.3670%) was achieved using Bior3.1for record number 115. The lowest percent root-mean-square different (PRD=0.61511%) was achieved using sym8 for record no. 117. The correlation coefficients (CC) for all the records in 9th iteration are very excellent (CC>99.99%). But it is noted that the performance of the compression algorithm is dependent on CR, PRD and CR together. Because of it, the highest compression performance was achieved for record 219 using Bior3.1 with a CR of 13.9839%, a PRD value of 0.71706% and CC=99.998%. The fonts of the other better performances are boldface in Table 3. (e.g. For record 219 using Sym8 wavelet, CR=11.92%, PRD=0.75792%, CC=99.997%. For record 119 using Bior3.1 wavelet, CR=13.2362%, PRD=0.86724%, CC=99.996%. For record 117 using Sym8, CR=9.3014%, PRD=0.61511%, CC=99.998%)

Table 3. Results of the proposed algorithm in 9th iteration of quantization using bior, db and sym wavelets for 11 records with n=2048 samples.

Record	Wavelet	PRD	CR	CC
101	Bior3.1	1.0904	9.0802	99.994
	db3	0.79744	6.3710	99.997
	Sym8	0.77716	6.5204	99.997
103	Bior3.1	1.2863	13.579	99.992
	db3	0.9922	7.2788	99.995
	Sym8	0.92422	7.4057	99.996
105	Bior3.1	0.9803	9.3361	99.995
	db3	0.83652	6.4366	99.997
	Sym8	0.8343	6.8767	99.997
115	**Bior3.1**	**1.0748**	**15.3670**	**99.995**
	db3	0.77459	7.9915	99.997
	Sym8	0.66418	8.4851	99.998
117	**Bior3.1**	**0.82503**	**11.976**	**99.997**
	db3	0.65117	8.7658	99.998
	Sym8	**0.61511**	**9.3014**	**99.998**
118	Bior3.1	0.99121	11.5174	99.995
	db3	0.78613	8.5043	99.997
	Sym8	0.74643	9.4655	99.997
119	**Bior3.1**	**0.86724**	**13.2362**	**99.996**
	db3	0.95186	12.385	99.996
	Sym8	**0.84927**	**12.564**	**99.997**
201	Bior3.1	1.0062	8.7419	99.995
	db3	0.870	6.3459	99.996
	Sym8	0.8044	6.2456	99.996
205	Bior3.1	1.0027	12.2835	99.995
	db3	0.7189	7.3048	99.997
	Sym8	0.6457	7.4596	99.997
213	**Bior3.1**	**0.97583**	**14.0888**	**99.996**
	db3	1.076	9.398	99.995
	Sym8	0.8379	9.1436	99.997
219	**Bior3.1**	**0.71706**	**13.9839**	**99.998**
	db3	0.79073	10.591	99.997
	Sym8	**0.75792**	**11.92**	**99.997**

It can be found from comparison of Table 3 and Table 4 that the values of CR and PRD decreased and the value of CC increased, when the numbers of iteration become higher. In other words, in the higher numbers of iteration, the PRD and CC performances become better values and the value of CR would be worse. Table 4 shows the achieved results for compression of the 8th iteration. The highest compression ratio (CR=23.6639%) was achieved using Bior3.1for record no. 115. The lowest percent root-mean-square different (PRD=0.97044%) was achieved using sym8 for record no. 117. The correlation coefficients (CC) for most of the records in 9th iteration are very excellent (CC>99.99%). But generally, the performance of the compression algorithm is dependent on CR, PRD and CR together. The highest compression performance was achieved for record 219 using Bior3.1 wavelet with CR=18.3154%, PRD=1.1508% and CC=99.994%. And the other better performances are highlighted with boldface in Table 4. As seen from Table 4, some better performances are: record 219 using Bior3.1 wavelet with values of CR=11.18.3154%, PRD=1.508% and CC=99.997%. Record 119 using db3 wavelet has the values of CR=21.293%, PRD=1.5276% and CC=99.989%.

Table 4. Results of the proposed algorithm in 8ᵗʰ iteration of quantization using bior, db and sym wavelets for 11 records with n=2048 samples

Record	Wavelet	PRD	CR	CC
101	Bior3.1	1.8531	12.7349	99.984
	db3	1.4949	8.3437	99.989
	Sym8	1.4288	8.4248	99.99
103	**Bior3.1**	**2.0404**	**23.1056**	**99.981**
	db3	1.7544	10.5419	99.985
	Sym8	1.5949	10.805	99.988
105	Bior3.1	1.6608	12.9994	99.987
	db3	1.5959	8.688	99.988
	Sym8	1.4987	9.0184	99.989
115	**Bior3.1**	**1.7895**	**23.6639**	**99.986**
	db3	1.3072	12.2768	99.992
	Sym8	1.0826	13.0220	99.994
117	Bior3.1	1.3217	15.8648	99.992
	db3	1.0714	13.474	99.994
	Sym8	**0.97044**	**13.9234**	**99.995**
118	Bior3.1	1.7186	15.7980	99.986
	db3	1.3365	11.2359	99.991
	Sym8	1.2392	11.6846	99.993
119	**Bior3.1**	**1.4276**	**18.4052**	**99.991**
	db3	**1.5276**	**21.293**	**99.989**
	Sym8	**1.3519**	**18.405**	**99.992**
201	Bior3.1	1.668	10.3959	99.987
	db3	1.6522	7.855	99.986
	Sym8	1.5066	7.66	99.989
205	Bior3.1	1.6166	14.5342	99.988
	db3	1.2902	11.038	99.991
	Sym8	1.1059	12.041	99.994
213	**Bior3.1**	**1.7402**	**18.0224**	**99.987**
	db3	1.8256	12.6990	99.985
	Sym8	1.4005	12.2636	99.991
219	**Bior3.1**	**1.1508**	**18.3154**	**99.994**
	db3	1.2499	13.812	99.993
	Sym8	1.1804	13.695	99.994

Table 5. Results of the proposed algorithm in 7ᵗʰ iteration of quantization using bior, db and sym wavelets for 11 records with n=2048 samples.

Record	Wavelet	PRD	CR	CC
101	Bior3.1	2.9383	20.592	99.96
	db3	2.4508	14.3949	99.972
	Sym8	2.4005	14.1596	99.973
103	**Bior3.1**	**3.1764**	**31.508**	**99.958**
	db3	2.8022	23.7137	99.964
	Sym8	**2.46**	**23.369**	**99.973**
105	Bior3.1	2.7537	23.011	99.965
	db3	2.6366	15.16	99.967
	Sym8	2.4623	14.054	99.972
115	**Bior3.1**	**2.9269**	**38.708**	**99.965**
	db3	2.0547	20.8207	99.981
	Sym8	**1.6648**	**17.0667**	**99.987**
117	**Bior3.1**	**2.1866**	**24.702**	**99.978**
	db3	**1.6835**	**20.8400**	**99.987**
	Sym8	**1.5128**	**20.5173**	**99.99**
118	Bior3.1	2.8922	20.295	99.962
	db3	2.2309	15.9096	99.977
	Sym8	2.116	16.7744	99.98
119	Bior3.1	2.3023	29.068	99.977
	db3	**2.3733**	**29.526**	**99.976**
	Sym8	**2.1324**	**28.373**	**99.981**
201	Bior3.1	2.8736	17.015	99.962
	db3	2.8425	11.642	99.962
	Sym8	2.5968	10.723	99.969
205	Bior3.1	2.718	23.345	99.967
	db3	2.0757	14.4410	99.98
	Sym8	1.6757	13.0521	99.987
213	Bior3.1	2.9586	29.0684	99.963
	db3	3.0349	17.6138	99.960
	Sym8	2.3647	16.9129	99.976
219	**Bior3.1**	**1.8968**	**27.077**	**99.985**
	db3	2.0768	20.574	99.981
	Sym8	**1.9614**	**23.273**	**99.983**

Table 5 shows the achieved results for compression of the 7ᵗʰ iteration. The best compression ratio (CR=38.708%) was achieved using Bior3.1for record no. 115. The lowest percent root-mean-square different (PRD=1.5128%) was achieved using sym8 for record no. 117. The highest correlation coefficient (CC) was obtained using sym8 wavelet for record number 117. But the performance of the compression is dependent on CR, PRD and CR. With this explanation, the highest compression performance was achieved for record 219 using Bior3.1 wavelet with CR=27.077%, PRD=1.8968% and CC=99.985%. It can be found from the table, some better performances are: record 115 using Bior3.1 wavelet with CR=38.708%, PRD=2.9269%, CC=99.965%. Record 117 using sym8 wavelet with CR=20.5173%, PRD=1.5128%, CC=99.99%. Record 219 using Bior3.1 wavelet with the values of CR=27.077%, PRD=1.8968%, CC=99.985%.

Table 6 and 7 show the simulation results of the proposed algorithm for 6ᵗʰ and 5ᵗʰ iterations. In these iterations, the values of CR and PRD are higher and the value of CC is lower. On the other hands, in the 6ᵗʰ and 5ᵗʰ numbers of iteration, the CR performance become better values and the values of PRD and CC would be worse. For iterations lower than 5, the compression ratio (CR) was achieved extremely high (the high CR is our favorite) but the percent root-mean-square different (PRD) that is a very important factor, was inferior (the value of PRD become high too whereas the low PRD is our preferable). And also for iterations higher than 9, the percent root-mean-square different (PRD) was obtained extremely low (the lower PRD is our admirable) but in these iterations, the compression ratio (CR) was achieved lower whereas the low CR is inferior. Because of it, we show the simulation results from 5ᵗʰ to 9ᵗʰ iteration.

Table 6. Results of the proposed algorithm in 6ᵗʰ iteration of quantization using bior, db and sym wavelets for 11 records with n=2048 samples.

Record	Wavelet	PRD	CR	CC
101	Bior3.1	4.6081	33.775	99.908
	db3	3.6798	28.3371	99.939
	Sym8	3.5737	23.5402	99.944
103	**Bior3.1**	**5.3956**	**45.056**	**99.889**
	db3	4.0371	29.2952	99.932
	Sym8	3.597	25.484	99.95
105	**Bior3.1**	**4.2107**	**38.509**	**99.925**
	db3	3.9489	21.435	99.931
	Sym8	3.8968	22.825	99.935
115	**Bior3.1**	**4.666**	**48.657**	**99.923**
	db3	3.1341	33.3748	99.959
	Sym8	2.7054	27.676	99.969
117	**Bior3.1**	**3.5025**	**46.739**	**99.948**
	db3	**2.5686**	**34.2892**	**99.971**
	Sym8	**2.3483**	**34.1851**	**99.976**
118	Bior3.1	4.8978	32.649	99.896
	db3	3.6659	21.9785	99.938
	Sym8	3.4013	20.9563	99.949
119	**Bior3.1**	**3.8009**	**42.187**	**99.942**
	db3	**3.9123**	**35.145**	**99.939**
	Sym8	**3.4618**	**34.618**	**99.951**
201	Bior3.1	4.5205	28.48	99.911
	db3	4.4088	21.851	99.915
	Sym8	4.1462	18.868	99.923
205	Bior3.1	4.4083	37.547	99.917
	db3	3.3845	26.5035	99.948
	Sym8	2.9333	21.1332	99.963
213	Bior3.1	4.8451	34.765	99.906
	db3	5.0816	22.3714	99.893
	Sym8	3.946	20.8786	99.935
219	**Bior3.1**	**3.2694**	**40.085**	**99.96**
	db3	3.378	29.031	99.953
	Sym8	3.1351	26.755	99.96

Table 7. Results of the proposed algorithm in 5ᵗʰ iteration of quantization using bior, db and sym wavelets for 11 records with n=2048 samples.

Record	Wavelet	PRD	CR	CC
101	Bior3.1	7.1957	48.974	99.802
	db3	5.4815	33.574	99.879
	Sym8	5.4879	29.3716	99.883
103	Bior3.1	9.2081	52.883	99.704
	db3	6.6052	32.1829	99.839
	Sym8	6.0897	32.602	99.869
105	Bior3.1	6.433	45.976	99.841
	db3	6.4408	36.75	99.824
	Sym8	6.216	33.474	99.848
115	Bior3.1	8.0969	59.441	99.783
	db3	**4.9235**	**42.1873**	**99.908**
	Sym8	4.3565	39.72	99.927
117	**Bior3.1**	**5.3753**	**53.007**	**99.902**
	db3	**4.1879**	**45.8819**	**99.931**
	Sym8	**3.8068**	**42.1873**	**99.951**
118	Bior3.1	7.7908	50.398	99.759
	db3	5.8654	42.506	99.849
	Sym8	5.672	30.484	99.863
119	**Bior3.1**	**6.3292**	**53.384**	**99.848**
	db3	6.9183	47.932	99.817
	Sym8	5.9209	38.444	99.877
201	Bior3.1	7.0242	42.506	99.809
	db3	6.5277	31.508	99.829
	Sym8	6.3807	27.241	99.83
205	Bior3.1	7.1405	48.868	99.825
	db3	5.1001	33.9788	99.892
	Sym8	4.7871	30.8603	99.908
213	Bior3.1	8.3895	42.3459	99.731
	db3	8.7010	31.0303	99.697
	Sym8	6.8939	26.8831	99.815
219	**Bior3.1**	**5.5204**	**52.759**	**99.898**
	db3	5.6762	37.36	99.874
	Sym8	5.5653	31.289	99.886

Table 8. A comparison of the average of PRD and CR based on the different wavelets and iterations of quantization

| Iteration	Wavelet	PRD (%)	CR (%)
9ᵗʰ	Bior3.1	0.983370	12.108180
	db3	0.840505	8.306609
	Sym8	0.768781	8.671600
8ᵗʰ	Bior3.1	1.635209	16.712700
	db3	1.464164	11.932481
	Sym8	1.305449	11.903890
7ᵗʰ	Bior3.1	2.693036	25.853581
	db3	2.387445	18.603245
	Sym8	2.122491	18.025000
6ᵗʰ	Bior3.1	4.374991	38.949909
	db3	3.745418	27.601063
	Sym8	3.376809	25.174490
5ᵗʰ	Bior3.1	7.136664	50.049263
	db3	6.038873	37.717381
	Sym8	5.561527	32.959663

Table 8 shows the average values of the performance accuracy at 9ᵗʰ, 8ᵗʰ, 7ᵗʰ, 6ᵗʰ and 5ᵗʰ iterations for all the eleven records. Because the correlation coefficients (CC) for all the proposed records in all iterations are very excellent (CC>99%), we have only calculated the average values of the PRD and CR for Bior3.1, db3 and Sym8 wavelets. As expected, the PRD is generally low and the compression ratio (CR) is achieved low at higher iterations and for lower iterations, the PRD and CR values are achieved higher. It can be seen from the Table8, The best compression ratio (CR=50.17449%) was obtained using Bior3.1 and the lowest percent root-mean-square different was achieved (PRD=0.768781%) using sym8 wavelet for all the considered records. But as we mentioned before, the best

performance depends on both CR and PRD. Therefore according to the values, the Bior3.1 and sym8 are achieved the best performances. The lower PRDs are achieved by sym8 wavelet and the higher CRs are achieved by Bior3.1 for all the considered iterations.
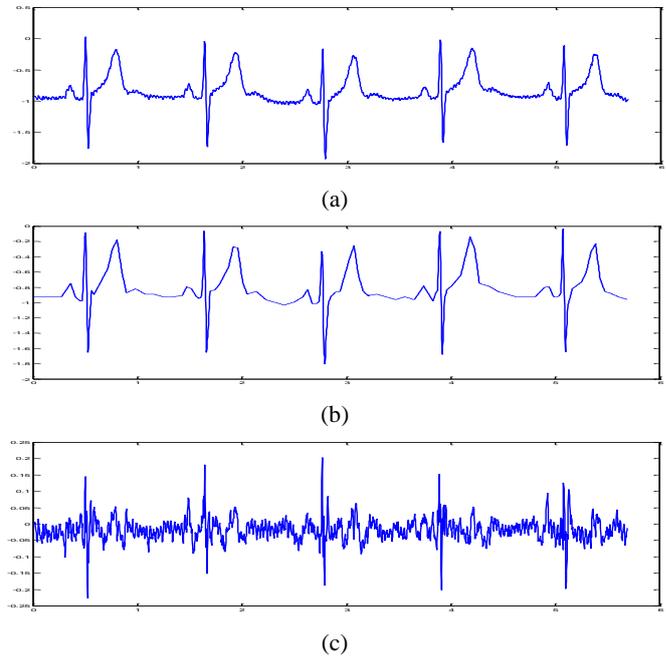
Figure 5. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using Bior2.2 wavelet and 2048 samples of signal and 5ᵗʰ iteration of quantization for record no. 117 from MIT-BIH database (CR=59.9149, PRD=4.2883, CC=99.928)
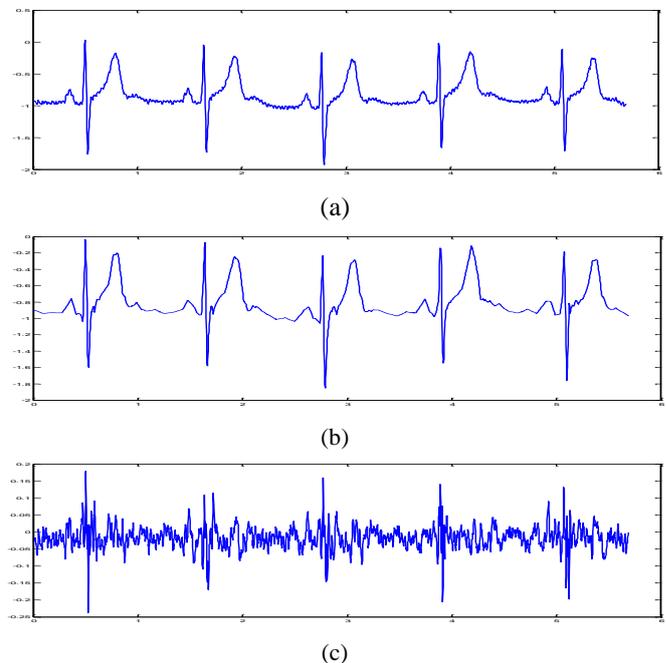
Figure 6. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using db3 wavelet and 2048 samples of signal and 5ᵗʰ iteration of quantization for record no. 117 from MIT-BIH database (CR=45.8819, PRD=4.1879, CC=99.931)
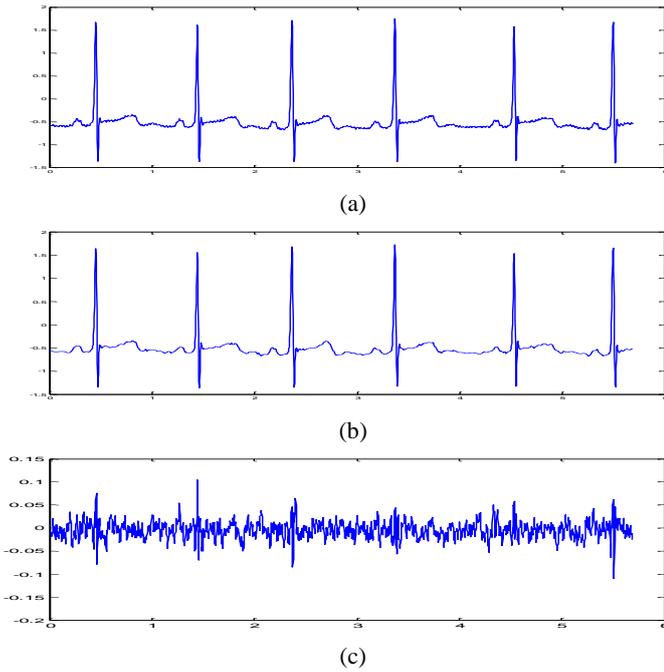
(a)

(b)

(c)

Figure 7. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using Bior3.1 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 115 from MIT-BIH database (CR=23.6639, PRD=1.7895, CC=99.986)
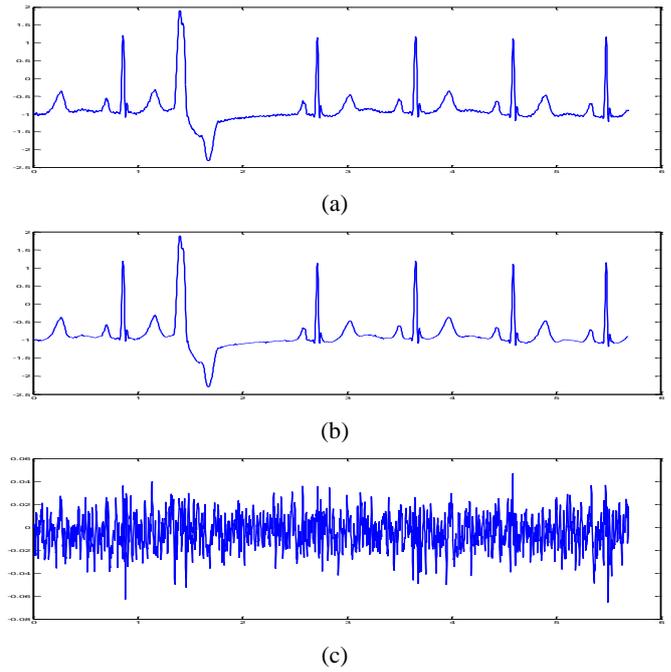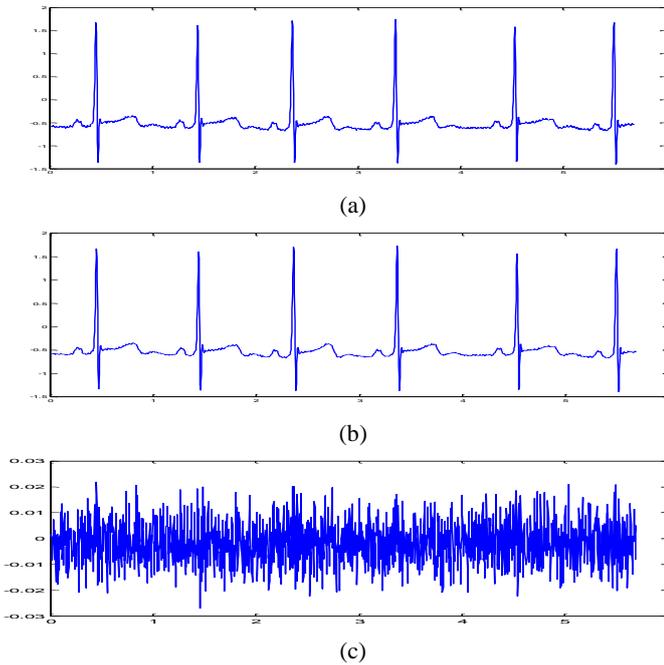

(a)

(b)

(c)

Figure 8. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using db3 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 115 from MIT-BIH database (CR=12.5925, PRD=1.1309, CC=99.994)
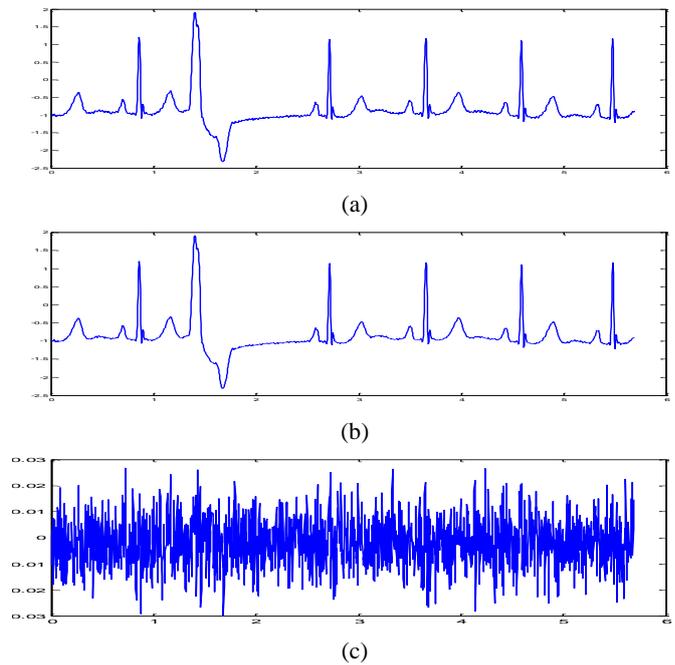

(a)

(b)

(c)

Figure 9. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using Bior4.4 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 119 from MIT-BIH database (CR=22.2170, PRD=1.4032, CC=99.991)

(a)

(b)

(c)

Figure 10. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using Sym7 wavelet and 2048 samples of signal and 9th iteration of quantization for record no. 119 from MIT-BIH database (CR=12.364, PRD=0.82527, CC=99.997)
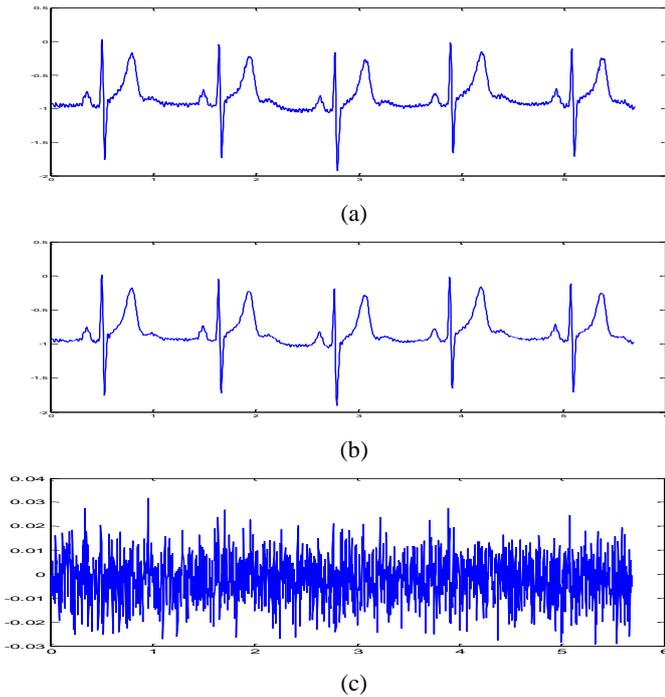
(a)

(b)

(c)

Figure 11. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using sym8 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 119 from MIT-BIH database (CR=13.923, PRD=0.97044, CC=99.995)
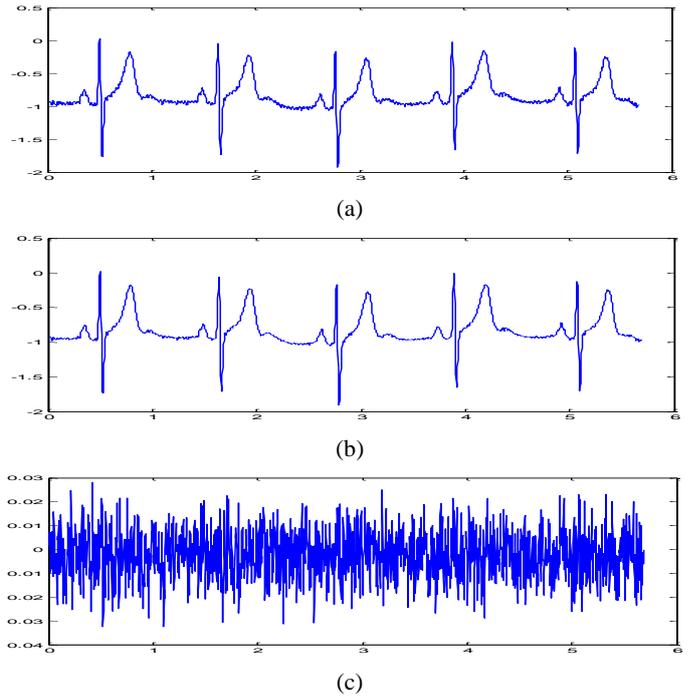

(a)

(b)

(c)

Figure 12. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using db2 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 117 from MIT-BIH database (CR=13.037, PRD=1.2312, CC=99.993)

(a)

(b)

(c)

Figure 13. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using sym5 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 117 from MIT-BIH database (CR=13.346, PRD=1.0594, CC=99.998)
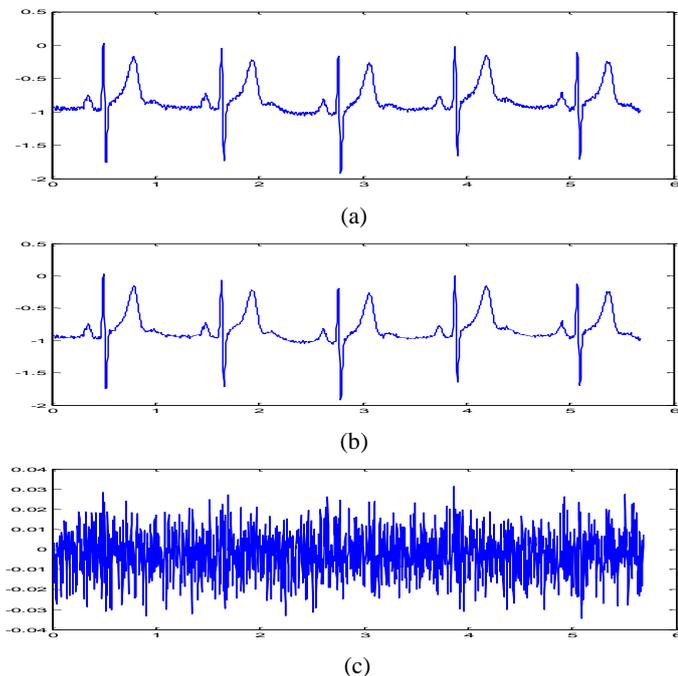

(a)

(b)

(c)

Figure14. (a) Original signal, (b) Reconstructed signal, (c) Error signal.

ECG compression using db2 wavelet and 2048 samples of signal and 8th iteration of quantization for record no. 117 from MIT-BIH database (CR=13.037, PRD=1.2312, CC=99.993)
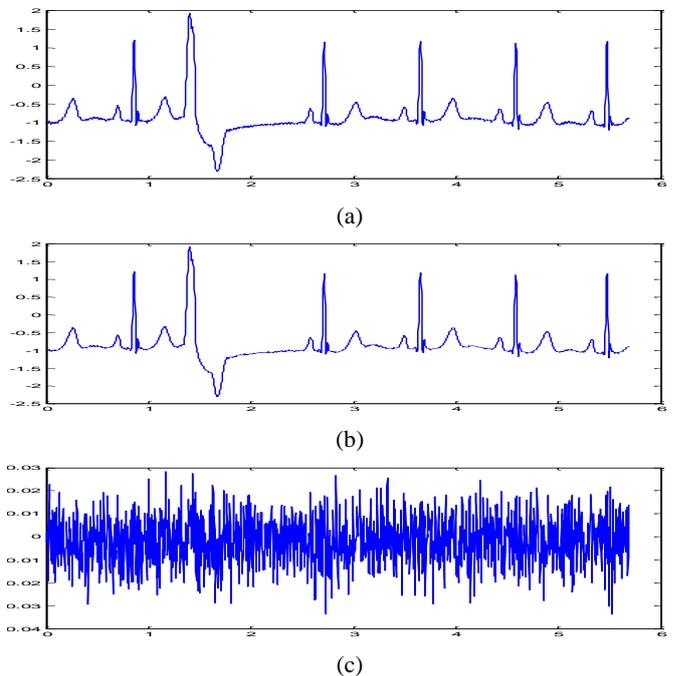
6. CONCLUSION

The proposed algorithm for compression of ECG signals using wavelet transforms and EZW& Huffman encoding based on the three-level quantization is described in this Paper. The algorithm is examined for compression of 11 records of ECG signal from the MIT-BIH database. The experimental results indicate that the presented wavelets in this coder have high performance. The some of biorthogonal wavelets have a performance better than the orthogonal wavelets. In this paper, combination of three-level quantization and EZW together for thresholding and encoding has been used. After selecting threshold, the three-level quantization has been continued from 1th level to 12th level of iteration. In low iterations, the values of CR and PRD are higher and the value of CC is lower. On the other hands, in the lower numbers of iteration, the compression ratio (CR) is achieved extremely high (CR become better values) but the percent root-mean-square different (PRD) that is a very important factor, is inferior (the value of PRD become high too whereas the low PRD is our favorite). And also for high iterations, the PRD is obtained extremely low (the lower PRD is our admirable) but in these iterations, the CR values are achieved lower whereas the low CR is inferior. Consequently, it seems reasonable to conclude that the best simulation results are achieved for 5th to 9th iterations. The three kinds of wavelet were tested to gain the acceptable results named: db, bior and sym.

The different results have gained for each wavelet and record number. Among all wavelets, in higher iterations, sym8 and some of biorthogonal wavelets (bior2.2, bior3.3, bior3.1 and bior4.4) achieved better results. Also, we have concluded that if high compression rates need, we should continue iterations of quantization for lower than 4th level. Consequently, if we want to decrease the PRD value, the iterations of the three-level quantizer can be continued to high levels. Generally, for values of CR>50 and 3.5<PRD, the three-level quantization should be continued to 4th or 5th level of iteration. If a ratio around 24<CR<50 and 1.5<PRD<3.5 is our favorite, we should repeat the three-level quantization to 6th or 7th iteration. For 6<CR<24 and 0.6<PRD<1.7, it should be quantized to 8th or 9th iteration. And for about 0<CR<10 and 0<PRD<0.6, the three-level quantization can be repeated to 10th or more. The number of iteration depends on our particular application in which value of CR and PRD should be used to gain our favorite results.

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