Australian Journal of Basic and Applied Sciences, 5(5): 739-749, 2011
ISSN 1991-8178

ECG Compression Using Subband Thresholding of the Wavelet Coefficients

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Abstract: This paper describes an efficient electrocardiogram (ECG) signal compression technique based on the combination of wavelet transform and thresholding of the wavelet coefficients according to their energy compaction properties in different sub bands to achieve high compression ratio (CR) with low percent root mean square difference (PRD). First, the ECG signal is wavelet transformed using different discrete wavelets. The wavelet transform is based on dyadic scales and decomposes the ECG signals into five detailed band levels and one approximation band level. Then, the wavelet coefficients in each subbands are thresholded using a threshold based on energy packing efficiency (EPE) of the wavelet coefficients. To assess the proper applicability of the proposed technique we have evaluated the effect of threshold levels selection on the quality of the reconstructed signal. To generalize the proposed method, the technique is tested for the compression of a large set of normal and abnormal ECG signals extracted from MIT-BIH database. The performance parameters of the compression algorithm are measured and a CR of 15.12:1 with PRD of 2.5% is achieved. Experiments on selected records from the MIT-BIH arrhythmia database reveal that the proposed method is significantly more efficient in compression than some existing wavelet based ECG compression method. The proposed compression scheme may find applications in digital Holter recording, in ECG signal archiving and in ECG data transmission through communication channels.

Key words: ECG Compression, EPE, Wavelet Transform, Thresholding, PRD.

INTRODUCTION

Signal compression plays a significant role in data communication systems. It yields a compact data presentation allowing efficient storage and transmission of information. A simple ambulatory ECG system with only one single lead, sampled at 360 samples/s and with 12- bit/sample resolution creates about 45 MB in 24 h. The compression of biomedical signals is very much important due to tremendous amount of data. Applications focusing on portable devices for 24-hour on-line cardiac monitoring are in increasing demand. However, serious difficulties are encountered in attempting to reduce the channel costs and electronic resources. Several attempts have been made which partly solve the problem using compression algorithms Benzid et al., (2003). The performance improvements of the conventional compression algorithms are required for the continuous acquisition of electrocardiogram (ECG). The main goal of an optimized compression technique is to minimize the number of samples needed to transmit the ECG without losing the remarkable information of the original signal in order to achieve a correct clinical diagnosis.

Much work has been done in ECG compression with the blooming of sub-band and wavelet based methods (Djohan *et al.,* 1995; Hilton, 1997; Ahmed *et al.,* 2000; Benzid *et al.,* 2008) and discrete cosine transform based method Zigel *et al.,* (2000) in signal processing. There are a great number of wavelet compression techniques available in the literature. However, the search for new methods and algorithms continues to achieve higher compression ratio while preserving the clinical information content in the reconstructed signal. Naturally, the clinical acceptability of the reconstructed signal depends on the intended data application and the common way to measure it through visual inspection. The use of the percent root mean square difference (PRD) has become common practice to the scientific community as a measure of fidelity of any ECG compression algorithm. Weighted diagnostic distortion (WDD) measure Donoho and Johnstone, (1995) is another method recently being investigated although it needs the subjective test by expert physiologists. In our proposed

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method, the evaluating criterion is based on PRD measurement for its simplicity and easy to calculate. Moreover, it is the most popular reported measure in the open literatures, which make easier the comparison between results of the developed and other methods.

Transform based compression using the wavelet transform (WT) is an efficient and flexible scheme. Since WT results large runs or zeros in the transformed signal, it can be efficiently used for compression. Moreover, the nonzero small coefficients can be thresholded using appropriate techniques with a further increase in the number of zeros. Hence, improvement in the compression ratio is expected. In technical literature there exist a large number of thresholding techniques. Among them the universal thresholding Yip and K. R. Rao, (1978), and thresholding methods based on energy packing efficiency Tohumoglu and Erbil Sezgin, (2007) are the most efficient methods. In the process of thresholding, there is the need of compromise between compression ratio and the quality of the reconstructed signal (Ahmed *et al.,* 2000; Tohumoglu and Erbil Sezgin, 2007).

This paper presents a very effective algorithm for an ECG compression system using wavelet transform and thresholding technique based on energy packing efficiency (EPE). As the WT decomposes the ECG signal into multi-resolution bands, a multi-level thresholding strategy based on EPE is applied in this paper. The algorithm can be tuned to required compression ratio and PRD by selecting thresholds based on a desired EPE. This paper is organized as follows: Section 2 presents a brief introduction to the wavelet transform and its implementation while the concept of signal thresholding is discussed in section 3. A brief description of the proposed compression algorithm is explained in section 4. The algorithm is tested on large set of records extracted from MIT-BIH arrhythmia database (BMECTR010, 1992), the results and comparisons with other compression algorithm in the literature are described in Section 4. Finally, Section 6 concludes this paper.

Methods:

Wavelet Transform:

Wavelet Transform analyzes 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 wavelet transform overcomes the fixed resolution analysis of the Short Time Fourier Transform (STFT). This makes the wavelets an ideal tool for analyzing signals with discontinuities or sharp changes, while their compactly supported nature enables temporal localization of signals' features. A wide variety of functions can be chosen as mother wavelet provided the admissibility and regularity conditions are satisfied Sheng, (1996). A mother wavelet $\psi(t)$ is a function of zero average:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{1}$$

When this function is dilated by a factor of a, and translated by another scalar b, we get another wavelet denoted by $\psi^{a,b}(t)$ and given by:

$$\psi^{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

The wavelet transform $X_w(a,b)$ of a function $x(t)$ at a scale a and position b is computed by correlating $x(t)$ with the wavelet $\Psi^{a,b}(t)$

$$X_w(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} \bar{\psi}\left(\frac{t-b}{a}\right)x(t)\,dt \tag{3}$$

The transform that only uses the dyadic values of scale parameter a, and translation parameter b was originally called the discrete wavelet transform (DWT). The DWT is the digital implementation of Eqn. (3) and it is defined as:

$$DWT(m,k) = \frac{1}{\sqrt{a_0^m}}\sum_k x(k)\psi(a_0^{-m}n - kb_0) \tag{4}$$

Generally, there are no explicit formulas for the mother wavelet functions. Hence most algorithms concerning wavelets are formulated in terms of the filter coefficients. The similarity between DWT and filter banks suggests that $\psi(a_0^{-m}n - kb_0)$ is the impulse response of a low pass digital filter with transfer function $g(\omega)$.

Then by selecting $a_0 = 2$ or $a_0^{-m} = 1, \frac{1}{2}, \frac{1}{4}, \frac{1}{8},$ ....each dilation of $\psi(n)$. effectively halves the bandwidth of $g(\omega)$. In this case dilation parameter *a* and translation parameter *b* both take only discrete values. For *a* we choose the integer powers of one fixed dilation parameter $a_0 > 1$ i.e. $a = a_0^m$. Different values of *m* correspond to wavelets of different widths. It follows that the discretization of the translation parameter *b* should depend on *m*. Narrow (high frequency) wavelets are translated by small steps in order to cover the whole time range, while wider (lower frequency) wavelets are translated by larger steps. Since width of $\psi\left(a_0^{-m}t\right)$ is proportional to a_0^m , we choose therefore to discretize *b* by $b = kb_0a_0^m$ where $b_0 > 0$ is fixed and $k \in Z$.

Thresholding of Signals:

In the scope of signal compression, thresholding of a certain sub band coefficients is done by discarding all coefficients that are smaller than a suitable threshold value. This may induce some distortion in a certain aspect of the reconstructed signal. In most situations, the resulting distortion induced by thresholding is acceptable. In wavelet based signal compression, thresholding does not generate major distortion in the reconstructed signal because of the energy invariance property of orthonomal wavelet transform. Orthonormal property of mother wavelet decorrelates the highly correlated data in a signal maximally. Determining a suitable thresholding level for global thresholding or levels for sub band thresholding is the most key point in wavelet based compression methods. Medical signals (e.g., ECG) are extremely redundant in terms of information and are contaminated by noise from different sources. Denoising the signal by choosing an optimum threshold increase both the quality recovery and the compression ratio (CR). As denoising methods are an important and widely studied topic in processing ECG signals, a large number of threshold definitions and methods can be found in [12]. Donoho and Johnstone defined the universal threshold level for denoising signals in [7]. In [13], it has been mentioned that the global threshold of one dimensional signals is based on the tradeoff between the retained energy and the number of zeros in the transformed coefficients and the level dependent threshold are derived from Birge-Massart strategy by putting σ=1.5 in the equation $\lambda = \sigma\sqrt{2\log n}$, where n is the signal length and σ^2 is the noise variance. In wavelet noise reduction thresholding techniques, high CR can be achieved by setting zeros for the noisy parts of the signal Benzid *et al.,* (2003). An optimum level is established between setting a maximum threshold to discard the insignificant information and optimizing it to increase the zero values in wavelet coefficients vector and to minimize the distortion induced by thresholding i.e. the error between the original signal and the reconstructed signal. Common criteria for measuring the signal distortion are percentage-root-mean-square-difference (PRD), percent signal-to-noise ratio (PSNR), mean-square error (MSE) etc. The wavelet transform decomposes the signal into detail band coefficients and approximate band coefficients. These wavelet coefficients have high energy at low frequency and low energy at high frequency Averbush and Lazar, (1996). The lowest frequency band coefficients is the smallest band in size and it includes high amplitude approximation band coefficients. The wavelet coefficients other than the approximation band are detail band coefficients and have small magnitudes in compare to approximation band coefficients. Among all the wavelet coefficients, only a few coefficients contain information about the real signal while other coefficients are less important details. Most of the energy of original signal is captured by approximate coefficients of the lowest resolution band Biran and Breiner, (1995). So, medical signals such as ECG can be effectively compressed by extracting the high energy low frequency coefficients and some low energy high frequency coefficients which cannot be discarded inspite of their low magnitudes as they contain significant information about the original signal. Such an extraction can be effectively done by selecting suitable threshold based on energy compaction property of the wavelet coefficients.

ECG Compression Algorithm:

The block diagram of the proposed compression algorithm is shown in Fig. 1. The compression algorithm is composed of the preprocessing of original ECG signal followed by WT, energy calculation of wavelet coefficients and proper thresholding of the sub band coefficients. The ECG data of definite time duration is first divided into blocks, each block consisting of length N samples. Each block is then preprocessed to prepare the raw ECG data for further processing. Then, the resulting discrete time-series data are wavelet transformed into another set of sequences. The transformation process performs two operations, it de-correlates the highly correlated ECG samples and it also helps to determine the threshold level for each band of frequencies based on energy contents. After the wavelet transformation of the ECG signal of each block, the threshold level for each band is determined based on the energy distribution of the wavelet coefficients among bands. Then, the wavelet coefficients are thresholded with the determined threshold level for different sub bands. In ECG signal processing, we are allowed to lose some redundant information. This affects the quality of the signal's reconstruction. In the following subsections, detailed descriptions of the sub blocks of the ECG compression algorithm are given.

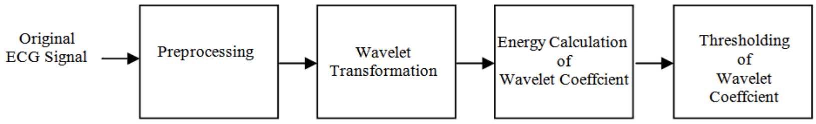


Fig. 1: The Block Diagram of the Compression Algorithm

Preprocessing:

This stage is of data processing is performed with an aim to increase the efficiency of the transformation processes and thus enhance the compression performance. First, the long ECG signal is segmented into short segments each of length N-samples. There are two main methods for the selection of segment length. The first method is to consider each heartbeat as one segment. The problem here is the heartbeat variability, so the detection of the QRS-complex and the knowledge of the RR period are necessary. However, this complicates the compression process and increases the computation burden. In the technical literature many segmentation criteria based on fixed length blocks have been introduced. The determination of the block (segment) size N is very much crucial as it determines the compression ratio and the corresponding PRD. A large N increases the variance of the sub band signal's distortion. By trial and error, a segment length of 2000 samples has been determined in this work and this size is found experimentally to give reasonable compression performance.

Wavelet Transformation of ECG Signal:

The output of the segmentation block is fed to the wavelet transform block. The preprocessed ECG signal is decomposed by using the discrete wavelet transform (DWT) up to the fifth level using biorthogonal (bior4.4) wavelet. The DWT up to the fifth level of decomposition has been chosen because in Ahmed *et al.,* (2000) it has been pointed out that the compression performance depends on the signal under test and the number of decomposition levels. It has been observed in preliminary simulation that the best performance can be obtained if the signal is decomposed up to the fifth level. Up to this level, the PRD decreases with the increase in the decomposition level. For signal compression, it is desired that the mother wavelet should have compact support, and the basis functions should be orthonormal and symmetric. Compact support makes the wavelet transform able to work on finite signals to discriminate signal features in both time and scale, while orthonormality is needed so as to maximally decorrelate the data in a signal Daubechies, (1992). The asymmetric property of wavelet filter can cause artifacts at borders of the wavelet sub bands. Biorthogonal wavelet families provide compact support, orthonormal and symmetric wavelets. Biorthogonal wavelets allows perfect reconstruction of the data using linear-phase filter banks, which in turn avoids reconstruction errors at the beginning and ending of data segments (Djohan *et al.,* 1995; Hilton, 1997).

The best filter is one that achieves the most retained energy of the original signal and a high CR with an acceptable PRD can be achieved. It has been noticed in (Djohan *et al.,* 1995; Hilton, 1997), the bior4.4 outperforms the others.

Thresholding of Wavelet Coefficients:

After the original signal is decomposed into its sub band components, an appropriate threshold level T is needed to control the compression ratio (CR). The selection of the threshold influences the effect of data compression directly. With a large threshold we can have high data reduction but poor quality of the reconstructed signal. On the other hand, a small threshold produces low data reduction but high signal fidelity. So, a threshold must be optimally chosen for ECG compression. In a normal cardiac cycle, the P wave occurs first, followed by the QRS complex and the T wave (Fig. 2).

The sections of the ECG between the waves and complexes are called segments and intervals: the PR segment, the ST segment, the TP segment, the PR interval, the QT interval, and the R-R interval. Intervals include waves and complexes, whereas segments do not. QRS complex, p wave and T wave are very important for clinical diagnosis whereas segments and intervals are not so important.

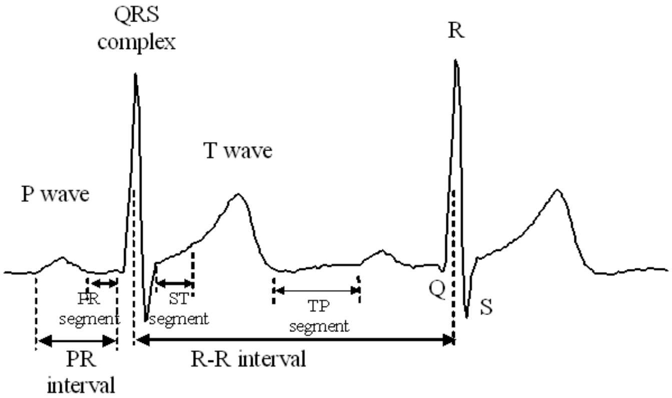


Fig. 2: Components of the ECG

Most of the energy of QRS complex, p wave and T wave concentrate in low frequency portion of complex and waves. Therefore, selecting different thresholds in different sub bands can improve the CR while preserving high data fidelity (i.e. low PRD). Since WT decomposes the signal into multi-frequency bands, the lowest frequency band (approximation band) is the smallest band in size and it includes high amplitude approximation coefficients. The detail coefficients, other than those of the approximation band, have small magnitudes and all these coefficients cannot be discarded for lossless compression of medical signals. Most of the energy is captured by approximate coefficients of the lowest frequency band. In this paper, the energy content in each sub band is used for the selection of the threshold level. The energy contribution of each wavelet decomposition sub band to the whole decomposition coefficients has been analyzed measuring the energy packing efficiency (EPE) Yip and Rao, (1978). This energy figure has been defined in many different ways. In this case, the EPE is a percentage quantity that presents a measure of the total preserved energy of a certain sub band after thresholding with respect to the total energy in that sub band before thresholding and is defined as

$$EPE(\%) = \frac{\sum_{n=1}^{L_i} (c(n))^2}{\sum_{n=1}^{L} (c(n))^2} \times 100 \tag{5}$$

where L_i and L are the number of coefficients in the th sub band after thresholding and the whole number of coefficients in that sub band before thresholding respectively.

To show the energy contribution of wavelet coefficients of different decomposition sub bands with respect to whole number of wavelet coefficients of the decomposed ECG signal, the wavelet transform was applied to decompose the first 2048 samples of the MIT-BIH database record 117 up to level five. The resulting EPE contribution for each sub-band is shown in Table 1. The EPE values for different decomposition sub bands have been determined by applying the Eqn. (5). By analyzing Table 1, we can see that about 99.58% of the total energy is concentrated in the 71 approximate coefficients and only 0.42% of the total energy in the remaining 1977 detail coefficients.

Table 1: EPE Values for the Decomposition Subbands of Record-117

Symbol of EPE for different subbands	Values of EPE in the respective sub-band
EPE_{D1}	0.0151
EPE_{D2}	0.0276
EPE_{D3}	0.02
EPE_{D4}	0.1386
EPE_{D5}	0.2181
EPE_{A5}	99.5806

The energy contribution of the approximation sub band to the total energy is 99.58%, and the energy contribution of the detail sub bands to the total energy is only 0.42%. The energy contribution of the detail sub band of level 5 is 52.01% of the total detail energy, which leaves 47.99% with the rest of the detail sub bands. Based on the above observations, in order to minimize the error in the reconstructed signal, we have applied the following thresholding technique based on EPE in different sub bands of the wavelet coefficients for compression purposes.

Thresholding Technique:

In this technique, the decomposition coefficients are thresholded by dividing the entire decomposition coefficients into six groups i.e. the approximations band coefficients (A_5) are kept without thresholding as they contain 99.51% of EPE of all the subbands which is shown in Table 1. We have calculated the threshold value for each detail subbands separately. This case will be termed distinct successive thresholding for details of each level. The following table shows an example for the selection of different values of γ_i% (EPEi) for this technique for the ECG signal decomposed up to the fifth level.

Table 2: EPE values in different subbands

Subbands	A_5	D_5	D_4	D_3	D_2	D_1
EPE(%)	100	98	95	90	80	50

In Al-Shrouf *et al.,* (2003), different thresholding techniques have been applied to compress ECG in which approximation band coefficients have been thresholded to obtain high CR, but we have examined that if the approximation band coefficients have been thresholded to obtain high CR, significant increasing of PRD has been noticed and some clinically important diagnostic information has been lost and there was a great difference between the original and reconstructed signal. By observing Table 1, it can be clearly verified. So, in our compression algorithm, the approximation band coefficients are not thresholded in order to obtain a desired CR with a corresponding low PRD so that all the clinically diagnostic information are preserved in the reconstructed signal and cardiologist can easily diagnose the reconstructed ECG signal.

To find the threshold level in each sub band, the energy (Ei) of the wavelet coefficients in that sub band is calculated. Then, the absolute of the wavelet coefficients in this sub band are sorted descending and the energy (E_{th}) of highest m coefficients is calculated. Here, m is the order of the coefficient at which, $E_{th} \leq 0.\gamma_i E_i$, where the percentage value of γ_i has been shown in Table2. The threshold level is the amplitude of the mth wavelet coefficient in the sorted list.

RESULTS AND DISCUSSIONS

In this section, computer simulation using MATLAB is generated and applied on a set of ECG signals in order to investigate the quality of the proposed compression technique.

Performance Measure:

The compression ratio (CR) and percent root mean square difference (PRD) will be used as a performance measure. The compression ratio (CR) is defined as

$$Compression\,Ratio = \frac{P \times B}{C} \tag{6}$$

where, P = Number of ECG samples,
B = Bit depth per sample and
C = Compressed ECG file size

The PRD is calculated using the mathematical expression:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}\left(x(n) - \hat{x}(n)\right)^2}{\sum_{n=1}^{N}(x(n))^2}} \times 100 \tag{7}$$

Where, $x(n)$ is the original signal, $\hat{x}(n)$ is the reconstructed signal, and N is the length of the window over which the PRD is calculated.

Simulation Results:

The compression algorithm was tested on a large set of records extracted from the MIT-BIH arrhythmia database Donoho and Johnstone, (1995). The records are 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 111, 112, 115, 116, 117, 118, 119, 121, 122, 123, 124, 200, 202, 205, 207, 209, 210, 214, 228 and 231.The results are obtained through simulation by MATLAB 7.0. Since MIT-BIH database has different types of ECG of different subjects, it is apparent that the performance of any compression algorithm will depend on the record. In literature, most authors used records 101, 117 and 119 to validate their algorithms. Threshold value calculation for record 117 by applying the above thresholding technique is given below:

Table 3: Exact value of approximate band coefficients

Index	1	2	3	4	5	6	7	8
Coefficient	-5.2345	-5.238	-5.2246	-5.2354	-5.2868	-5.39	-5.3783	-5.275
Index	9	10	11	12	13	14	15	16
Coefficient	-4.7679	-4.8377	-5.62	-4.2727	-2.9738	-1.8438	-4.809	-4.7544
Index	17	18	19	20	21	22	23	24
Coefficient	-5.1639	-5.2431	-5.2845	-5.3207	-4.9336	-5.0029	-4.7286	-5.4843
Index	25	26	27	28	29	30	31	32
Coefficient	-4.2937	-2.7614	-2.3791	-5.0586	-4.966	-5.4965	-5.7339	-5.8013
Index	33	34	35	36	37	38	39	40
Coefficient	-5.8206	-5.1861	-5.6231	-5.6563	-5.9043	-4.6331	-2.3331	-3.7785
Index	41	42	43	44	45	46	47	48
Coefficient	-5.1934	-5.1234	-5.4206	-5.4711	-5.4008	-5.3409	-4.7431	-4.8445
Index	49	50	51	52	53	54	55	56
Coefficient	-5.3013	-4.2978	-3.5177	-1.3574	-4.0006	-4.569	-4.862	-5.1544
Index	57	58	59	60	61	62	63	64
Coefficient	-5.278	-5.246	-5.2452	-4.5653	-5.172	-4.9465	-5.1346	-4.2038
Index	65	66	67	68	69	70	71	
Coefficient	-2.0635	-3.8221	-5.1003	-5.0421	-5.0961	-5.0685	-5.0139	

Table 4: Detail band coefficient of level 5 (D_5) after thresholding

Index	1	2	3	4	5	6	7	8
Coefficient	1.9039	1.8278	1.8072	1.196	0.70936	0.65258	0.63587	0.58436
Index	9	10	11	12	13	14	15	16
Coefficient	0.57761	0.50118	0.46989	0.42329	0.42039	0.41188	0.38074	0.36602
Index	17	18	19	20	21	22	23	24
Coefficient	0.30239	0.29634	0.29075	0.28359	0.27934	0.25229	0.24756	0.23723
Index	25	26-71						
Coefficient	0.20776	0						

Table 5: Detail band coefficient of level 4 (D_4) after thresholding

Index	1	2	3	4	5	6	7	8
Coefficient	2.0745	2.0413	1.8498	1.8468	1.0744	0.82832	0.72856	0.71729
Index	9	10	11	12	13-133			
Coefficient	0.63655	0.60795	0.51774	0.48131	0			

Table 6: Detail band coefficient of level 3 (D_3) after thresholding

Index	1	2	3	4	5	6	7	8
Coefficient	0.74931	0.74475	0.60308	0.56355	0.41151	0.32989	0.31176	0.30915
Index	9	10	11	12	13	14	15	16
Coefficient	0.28011	0.2513	0.22568	0.22064	0.18722	0.1844	0.1732	0.15451
Index	17	18-257						
Coefficient	0.1396	0						

By observing Table 3, it is seen that most of the coefficients have high amplitudes which absorbs major portion of the energy of original signal, Therefore, in our compression algorithm, these coefficients are not thresholded so that all the clinically diagnostic information are preserved in the reconstructed ECG signal. Only the amplitude values of the thresholded coefficients in detail band D_5-D_3 are shown from Table 4 to Table 6 and are sorted in descending order. It is apparent from these Tables, the threshold values of detail band D_5, D_4, and D_3 are 0.20776, 0.48131, 0.1396 respectively. After thresholding in detail band D_2, there exists only six significant coefficients in which the threshold value is 0.089791. In the similar manner the threshold value for detail band D_1 is calculated 0.094892. All the wavelet coefficients lower than the threshold values in each sub band (D_5-D_1) are discarded and are termed as insignificant coefficients. With the calculated threshold values, level thresholding is applied on record 117 through computer simulation using MATLAB 7.0 and a good CR of 15.12:1 with a corresponding low PRD 2.5% is achieved. Fig. 3 and Fig. 4 show the original ECG of record 117 and its wavelet coefficients.

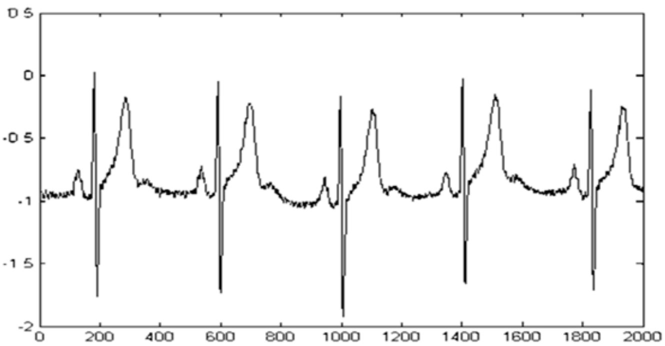


Fig. 3: Original signal of record-117

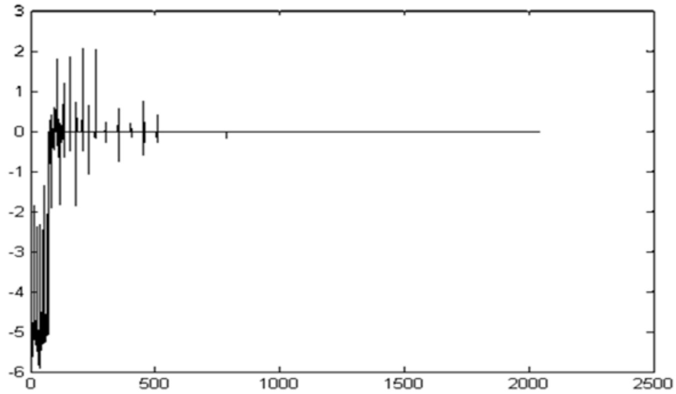


Fig. 4: Wavelet coefficients of record-117

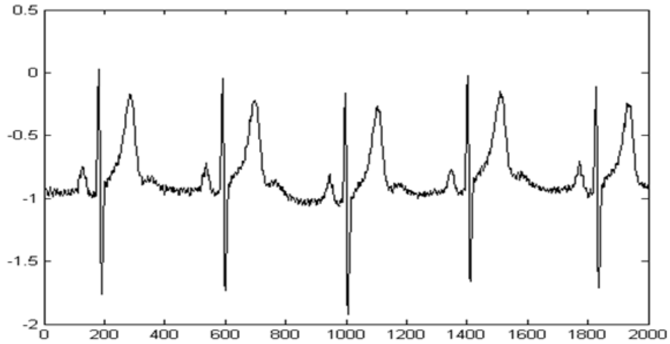
Comparison with Other Methods:

The compression algorithm can be used for most one dimensional non-stationary signals. For the sake of comparison with other methods (Djohan *et al.,* 1995; Hilton, 1997; Tohumoglu, and K. Erbil Sezgin, 2007; Al-Shrouf *et al.,* 2003; Boukhennoufa *et al.,* 2009), ECG signals extracted from the MIT-BIH arrhythmia database are used for experimentation. For this purposes, the proposed compression algorithm has been applied for the same data sets used in (Djohan *et al.,* 1995; Hilton, 1997; Al-Shrouf *et al.,* 2003; Boukhennoufa *et al.,* 2009) record 117 and in (Tohumoglu and Erbil Sezgin, 2007) record 101 of the database. It can be seen from Table 7 that the compression algorithm can compress ECG data better than the mentioned with previous methods.

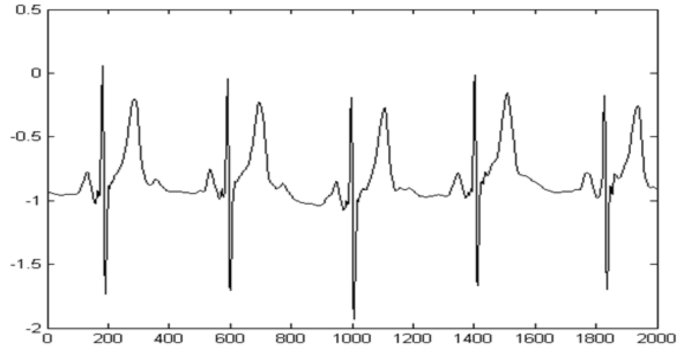
Table 7: Comparison of the Compression Algorithm with other Algorithms

Algorithm	MIT-BIH Database	PRD (%)	CR
Boukhennoufa [18]	117	2.43	14.31
Al-Shrouf [17]	117	5.3	11.60
Tohumoglu [9]	101	5.83	14.90
Hilton [3]	117	2.6	8.00
Djohan [2]	117	3.9	8.00
Proposed	101	3.84	12.52
Proposed	117	2.5	15.12

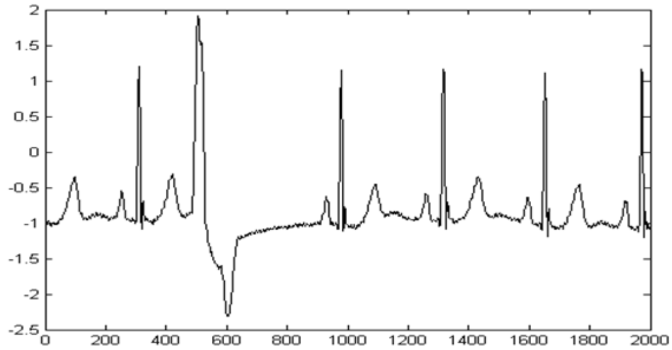
The lower percent root-mean-square difference obtained in our experiment offers less visual distortion in the reconstructed signal suggesting it is one of the best compression methods in ECG compression. Fig. 5 illustrates the original ECGs and reconstructed ones of records 117 and 119 when the compression algorithm is adopted.



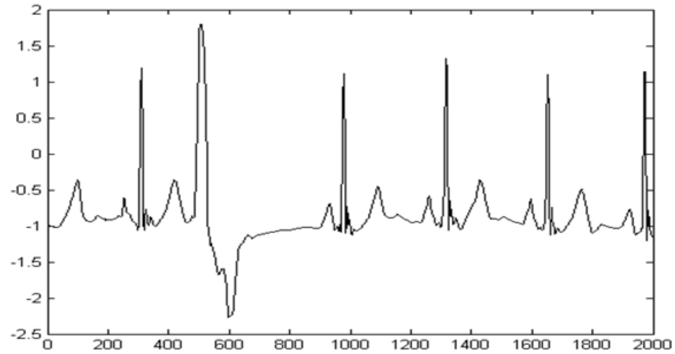
(a)



(b)



(c)



(d)

Fig. 5: (a) Original Signal Record-117
(b) Reconstructed Signal Record-117
(c) Original Signal Record-119
(d) Reconstructed Signal Record-119

Conclusion:

Data compression of ECG signals allows long-term digital storage and archiving of ECG recordings. A simple lossy compression algorithm for ECG signals based on subands thresholding of the wavelet coefficients is experimented. It compacts as much of the signal energy into as few coefficients as possible. The performance parameters of the compression technique using the applied thresholding strategy are measured and a compression ratio of 15.12 is achieved with a PRD of 2.5%. This yields a substantial reduction in ECG signal bandwidth in the telemedicine applications and an increased storage capacity of the digital ambulatory recorders. These results are significantly better than those of conventional ECG compression systems. The rate/distortion performance of the algorithm can be controlled by selecting thresholds based on desired EPE values. All the clinical information is preserved after compression and this makes the algorithm safe to be used to compress ECG signals. Further improvement in the compression ratio can be expected with more sophisticated and efficient entropy encoders. Another possibility that might improve the compression performance is to develop a new hybrid technique based on the combination of wavelet transform and linear prediction of the wavelet coefficients. This case is now under consideration.

ACKNOWLEDGMENTS

This workhas been supported by the Department of Electrical, Electronics and System Engineering, UKM, Malaysia and by NPST Programby King Saud University, Saudi Arabia, Project Number: 10-ENE1039-02.

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