

# ECG Signal Compression using Energy Compaction Based Thresholding of the Wavelet Coefficients

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## ABSTRACT

A wavelet-based method for the compression of electrocardiogram (ECG) signal is presented. The original ECG signal are firstly preprocessed after that the preprocessed signal is digitized. The discrete wavelet transform (DWT) is applied to the digitized ECG signal; then the resulting wavelet coefficients are thresholded using a threshold based on energy packing efficiency of the wavelet coefficients. The proposed algorithm reduces the bit rate of ECG and preserves its main clinically diagnostic features by minimizing reconstructed signal distortion. To assess the technique properly we have evaluated the effect of threshold levels selection on the quality of the reconstructed signal. The technique is tested for the compression of a large set of normal and abnormal ECG signals extracted from MIT-BIH arrhythmia database, which generalizes the ultimate thresholding method. The performance parameters of the compression algorithm are measured and a compression ratio of 14.55:1 with percent root mean square difference (PRD) of 2.56% is achieved. Experiments on several records from the MIT-BIH database showed that the proposed algorithm outperforms the other well-known wavelet-based ECG compression algorithm.

**Keywords:** ECG Compression, Wavelet Transform, Thresholding, energy packing efficiency, PRD.

## 1. INTRODUCTION

The purpose of ECG compression is to reduce the amount of bits needed to transmit, to store digitized ECG data as much as possible with a reasonable implementation of complexity while maintaining clinically acceptable signal quality. 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 [1]. 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.

Transform based compression using the wavelet transform (WT) is an efficient and flexible scheme. With the blooming of sub-band and wavelet based methods in signal processing, much work has been done in ECG compression using these techniques [2]-[4]. There is 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 is another method recently being investigated although it needs the subjective test by expert physiologists.

Recently developed wavelet transforms have become an attractive and efficient tool in many applications especially in coding and compression of signals. This results from their multi-resolution and high-energy compaction properties. Wavelet transform can be viewed as a block transform with overlapping basis functions of variable lengths. Basic wavelet theory may be found in Daubechies's book [5], while wavelet applications may be found in Meyer's book [6]. 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 [7], and thresholding methods based on energy packing efficiency [8] 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 [4].

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 multiresolution 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. Section 3 presents the compression algorithm. The algorithm is tested on large set of records extracted from MIT-BIH arrhythmia database [9], the results and comparisons with other compression algorithm in the literature are presented in Section 4. Finally, Section 5 concludes this paper.

## 2. 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 [10]. A mother wavelet  $\psi(t)$  is a function of zero average:

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

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:

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

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  $\psi^{a,b}(t)$

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

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:

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

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  $a_0^{-m} = 1, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \dots$  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  $\psi(a_0^{-m}t)$  is proportional to  $a_0^m$ , we choose therefore to discretize  $b$  by  $b = kb_0 a_0^m$  where  $b_0 > 0$  is fixed and  $k \in Z$ .

## 3. ECG COMPRESSION ALGORITHM

The compression algorithm is composed of the preprocessing of original ECG signal followed by WT, energy calculation of wavelet coefficients and proper thresholding of 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.

### 3.1 Preprocessing

This stage 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.

### 3.2 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 [4] 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. The asymmetric property of wavelet filter can cause artifacts at borders of the wavelet sub bands. Biorthogonal wavelet families, with their orthonormal and symmetric properties, provide compact support. These wavelets allow perfect reconstruction of the data using linear-phase filter banks, which in turn avoids reconstruction errors at the beginning and end of data segments [2, 3].

### 3.3 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. 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 can not 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) [8]. 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

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

where  $L_i$  and  $L$  are the number of coefficients in the  $i$ 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 subband to the total energy is 99.58%, and the energy contribution of the detail subbands to the total energy is only 0.42%. The energy contribution of the detail subband of level 5 is 52.01% of the total detail energy, which leaves 47.99% with the rest of the detail subbands. 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.

In this thresholding technique, the decomposition coefficients are divided into three groups which are: a) the detail band coefficients ( $D_5$ ) of level five, b) the detail band coefficients ( $D_4$ ) of level four and c) the coefficients comprising the detail subbands  $D_3$ ,  $D_2$  and  $D_1$ . Each group is thresholded using a threshold that is selected at certain desired  $EPE_i$  (%). Table 2 shows an example for the selection of different values of  $\gamma_i$ % ( $EPE_i$ ) for this technique for the ECG signal decomposed up to the fifth level. It is worth noting point from table 2 that the EPE values for sub bands  $D_5$  and  $D_4$  are very near. Because the highest magnitude coefficient value of  $D_4$  is greater than the highest magnitude coefficient value of  $D_5$ . If the difference

is significant then all the diagnostic clinical information in the reconstructed signal cannot be preserved.

**Table 2:** EPE Values of different sub bands

Sub bands	A <sub>5</sub>	D <sub>5</sub>	D <sub>4</sub>	D <sub>3</sub> - D <sub>1</sub>
EPE(%) for Different subbands	100	98	97	85

To find the threshold level in each sub band, the energy (E<sub>i</sub>) 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<sub>th</sub>) of highest m coefficients is calculated. Here, m is the order of the coefficient at which, E<sub>th</sub> ≤ 0. γ<sub>i</sub>E<sub>i</sub>, where the percentage value of γ<sub>i</sub> has been shown in Table 2. The threshold level is the amplitude of the mth wavelet coefficient in the sorted list

**4. RESULTS AND PERFORMANCE ANALYSIS**

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.

**4.1 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

$$CompressionRatio = \frac{P \times B}{C} \tag{6}$$

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:

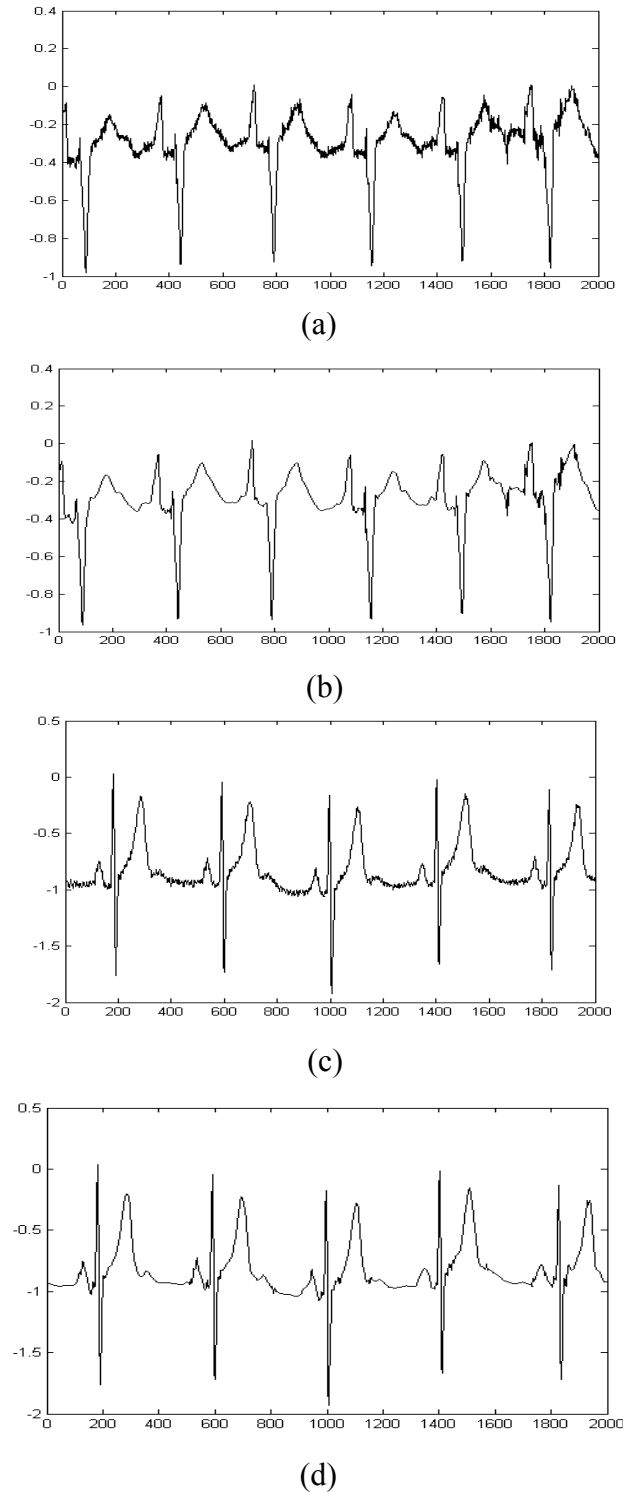
$$PRD = \sqrt{\frac{\sum_{n=1}^N (x(n) - \hat{x}(n))^2}{\sum_{n=1}^N (x(n))^2}} \times 100 \tag{7}$$

where, x(n) is the original signal, x̂(n) is the reconstructed signal, and N is the length of the window over which the PRD is calculated.

**4.2 Simulation Results**

The compression algorithm was tested on a large set of records extracted from the MIT-BIH arrhythmia database [9]. 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.

Fig.1 illustrates the original ECGs and reconstructed ones of records 108 and 117 when the compression algorithm is adopted. 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 117 and other suitable records to validate their algorithms.



**Fig. 1:** (a) Original Signal of Record 108  
 (b) Reconstructed Signal Record-108  
 (c) Original Signal Record-117  
 (d) Reconstructed Signal Record-117

### 4.3 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 [2], [3], [11], ECG signals extracted from the MIT-BIH arrhythmia database are used for experimentation. For this purposes, the proposed algorithm has been applied for the same data sets used in [2], [3], [11], records 117 of the database.

In [12], 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.

It can be seen from Table 3 that the proposed compression algorithm compresses ECG data better than the mentioned previous methods.

**Table 3:** Comparison of the Compression Algorithm with other Algorithms

Algorithm	MIT-BIH Database	PRD (%)	CR
Al-Shrouf [11]	117	5.3	11.6:1
Hilton [3]	117	2.6	8:1
Djohan [2]	117	3.9	8:1
Proposed	117	2.56	14.55:1

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 compression methods in ECG compression.

### 5. CONCLUSION

The feature of a wavelet transform based ECG compression algorithm is presented in this paper. Data compression of ECG signals allows long-term digital storage and archiving of ECG recordings. 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 strategies are measured and compression ratio of 14.55, is achieved with a PRD of 2.56%. 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. Selecting thresholds based on desired EPE values can control the rate/distortion

performance of the algorithm. All the clinical information is preserved after compression and this makes the algorithm safe to be used to compress ECG signals. The bit rate of the compression algorithm can be decrease by addition of Huffman coding to the thresholded wavelet coefficients. The future work is aimed towards this improvisation.

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