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ONE DIMENSIONAL SIGNAL COMPRESSION USING AN EFECTIVE THRESHOLDING TECHNIQUE THROUGH WAVELET TRANSFORM

M. Sharafat Hossain

ABSTRACT

This paper describes an effective thresholding strategy for the compression of one dimensional signal (such as electrocardiogram (ECG) signal) using wavelet transformation. A discrete wavelet transform (DWT) is applied to the digitized ECG signal. The DWT coefficients are first preprocessed, and then the preprocessed coefficients are thresholded using suitable threshold value or values to achieve a compression ratio (CR) with a corresponding low percent root mean square difference (PRD) which are the performance parameters of the proposed compression algorithm. The ability of the algorithm to compress ECG signals is investigated; the results were obtained by compressing and decompressing normal and abnormal ECG signals. Simulation results on several records from the MIT-BIH arrhythmia database show that the proposed compression algorithm outperforms some previously developed ECG compression algorithms.

Keywords: *ECG Compression, wavelet transform, thresholding, PRD*

INTRODUCTION

Compression of signals is based on removing the redundancy between the neighboring samples and/or between adjacent cycles (Bradie, 1996), (Held and Marshall, 1996), (Jalaledine *et al.*, 1990). In data compression, it is desired to represent data by as small as possible number of coefficients within an acceptable loss of visual 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 (Benzid *et al.*, 2003). ECG compression is a subject that is attracting much attention from many researchers. Digitized ECGs are most commonly used in applications such as monitoring and patient databases. The purpose of ECG compression is to reduce by as much as possible the number of bits of digitized ECG data that need to be transmitted or stored, with reasonable complexity of the implementation, while maintaining clinically acceptable signal quality. During the past few decades, many schemes for ECG compression have been proposed. As most of them do not reconstruct exactly the original signal when deccompressed, they are called lossy-compression techniques. Some authors (Lu *et al.*, 2000), (Nygaard *et al.*, 2001) have classified these techniques into two categories, namely direct methods and transform methods. However, some other literature, such as (Blanco-Velasco et al., 2004), have proposed a third category, "other methods", for those methods that cannot be included in the first two categories.

In the first category, the compression is done directly on the ECG samples in the time domain to reduce the redundancy among them. A good summary of these methods was presented in (Jalaledine *et al.*, 1990). Direct compression techniques are still under consideration by many researchers. A time domain algorithm was presented in (Nygaard *et al.*, 2001). This algorithm is based on the coding of line segments, which are used to approximate the ECG signal. These segments are then fitted in a way that is optimal in the rate distortion sense.

In the second category, the original samples are transformed to another domain in order to greatly reduce the correlation among the signal samples and to compact much of the signal energy into a

Department of Electrical and Electronic Engineering, Dhaka University of Engineering and Technology (DUET), Gazipur 1700, Bangladesh

small number of transform coefficients. In this way, many small transform coefficients can be discarded in the hope of achieving better lossy-compression performance. Among them, the recently developed wavelet transform based compression methods (Lu *et al*., 2000), (Djohan et al., 1995), (Hilton, 1997), (Al-Shrouf et al., 2003) have shown outstanding performance than all other transform methods. In most cases, direct methods are superior to transform methods with respect to the complexity of the system and the error control mechanism; however, transform methods usually achieve higher compression ratios and are insensitive to the noise contained in the original ECG signals (Djohan et al., 1995), (Hilton, 1997).

In the third category, the signals are either preprocessed to extract various parameters such as the QRS complex and long-term predictions, or divided into a set of spectral components by some kind of sub band decomposition technique for better compression. In (Blanco-Velasco et al., 2004), N-PR cosine modulated filter banks were applied for decorrelation of the input signals. The decorrelated signals were quantized by a threshold-based quantizer and then run-length coded. The analysis-by-synthesis ECG compressor (ASEC) (Zigel et al., 2000) performs PQRST complex segmentation, dependent nonuniform filtering, and feature extraction. By minimizing a weighted diagnostic distortion, the parameters of the best estimate of the original PQRST complex are obtained. The error residual is then vector quantized from a trained codebook. Among these techniques, methods based on the discrete wavelet transform (DWT) play an interesting role owing to their easy implementations and their efficiencies.

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 exists a large number of thresholding techniques. Among them the universal thresholding (Donoho and Johnstone, 1995) and thresholding methods based on energy packing efficiency (Yip and Rao, 1978) are the most efficient methods. In the process of thresholding, compromise needs between compression ratio and the quality of the reconstructed signal (Ahmed et al., 2000).

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 II presents a brief description of materials and methods of the compression algorithm. The algorithm is tested on large set of records extracted from MIT-BIH arrhythmia database (MIT-BIH Arrhythmia Database, 1992) the results and discussions with other compression algorithm in the literature are presented in Section III. Finally, Section IV concludes regarding the outcome of the paper.

MATERIALS AND METHODS

1. WAVELET TRANSFORM

Wavelet Transform (WT) 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. It 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 and Poularikas, 1996). A mother wavelet $\psi(t)$ is a function of zero average:

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

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 is given by:

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

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

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

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:

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

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 $a_0^{-m} = 1, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \ldots$ 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. Since width of $\psi(a_0^{-m}t)$ 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 $k \in Z$.

2. 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 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 the following subsections, detailed descriptions of the sub blocks of the ECG compression algorithm are given.

A. Preprocessing

The aim of this stage is 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. So, the input signal is divided into contiguous, nonoverlapping sample frames and transformed frame by frame. The frame size is 2000 samples, and biorthogonal 4.4 wavelet filters are used to implement a five-level discrete wavelet transform. Detail comments on the selection of these parameters, are mentioned in the following section.

B. 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 DWT up to the fifth level using biorthogonal (bior4.4) wavelet. The DWT up to the fifth level of decomposition has been chosen because (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 be orthonormal and symmetric. Compactly supported nature of wavelets enables temporal localization of signals' features to work on finite signals, while orthonormality property of wavelets ensures the maximum decorrelation of 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.

C. Thresholding of Wavelet Coefficients

The last stage of the compression algorithm concerns with the thresholding of the wavelet coefficients based on a desired EPE. The selection of the threshold influences the effect of data compression directly. Generally, a large threshold could attain high data reduction but poor signal fidelity. Otherwise, a small threshold would produce low data reduction but high signal fidelity. The suitable choice of the threshold is the key point of ECG data reduction. In this paper, the energy content in each sub band is used in the selection of the threshold levels. It is well known that ECG signals are non-stationary and every beat cycle consists of QRS complex, P-, T-, S-T-segments, base line and so on. The first three components are most useful in clinical diagnosis. The major energy of the QRS complex concentrates between 5-15 Hz, while the P and T waves are below 5 Hz. In recent years ventricular late potentials (VLPs) in the terminal part of the QRS complex have aroused great interest of physicians. Their frequency band is limited between 35-200 Hz**.** Therefore, different considerations in different scales must be given. In small scales, only QRS component and VLPs are useful. Usually the amplitude of QRS complex is large, so high thresholds in these scales could be selected in order to improve the data reduction. But in VLPs part, smaller thresholds should be chosen due to their low amplitudes. The P wave's amplitude is also small, but very important for clinical diagnosis. This information is only significant in some special cases. So smaller thresholds should be used in these scales in order to retain this information. Therefore, selecting different thresholds in different scales could improve the effect of data compression effectively while keeping a high data fidelity. Special attention must be also paid to the coarse (approximation), since it contains the ECG signal's low frequency and DC components. If the threshold level is chosen incorrectly for these components, the reduction efficiency will be reduced heavily. Dismissing the DC component before transformation can partially solve this problem.

In this paper, the threshold levels are selected in different sub bands based on the energy compaction property of the wavelet coefficients. 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

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

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(MIT-BIH Arrhythmia Database, 1992)

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

As 99.58% of the total signal energy is contributed by the approximation band wavelet coefficients, these coefficients are kept without thresholding and the detail band coefficients are divided into two groups which are: a) the detail band coefficients (D_5) of level five, and b) the coefficients comprising the detail sub bands D_4, D_3, D_2 and D_1. Each group is thresholded using a threshold that is selected at certain desired EPE_i (%).The following table shows an example for the selection of different values of γ_i% (EPE_i) for this technique for the ECG signal decomposed up to the fifth level.

Table 2. EPE Values Using The Thresholding Technique

Sub bands	A_5	D_5	D_4 - D_1
EPE(%) for Different subbands	100	98	95

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 values of the wavelet coefficients in this sub band are sorted in descending order and the energy (E_{th}) of highest k coefficients is calculated. Here, k 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 kth 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.

A. 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

$$Compression\ Ratio = \frac{P \times B}{C} \qquad (6)$$

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:

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

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.

B. Simulation Results

The compression algorithm was tested on several recordings extracted from the MIT-BIH arrhythmia database. All ECG signals in this database are sampled at 360 Hz. The resolution of each sample is 11 bits/sample. 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. Figure 1 and 2 illustrate the original ECGs and reconstructed ones of records 117 and 101 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 record 117 and other arbitrary records to validate their algorithms.

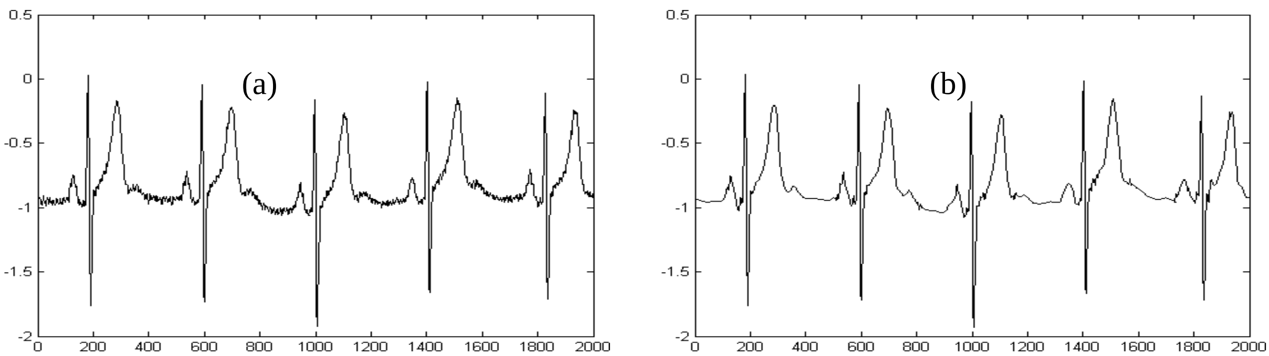

Figure 1. (a) Original Signal of Record 117 (b) Re Reconstructed Signal Record-117

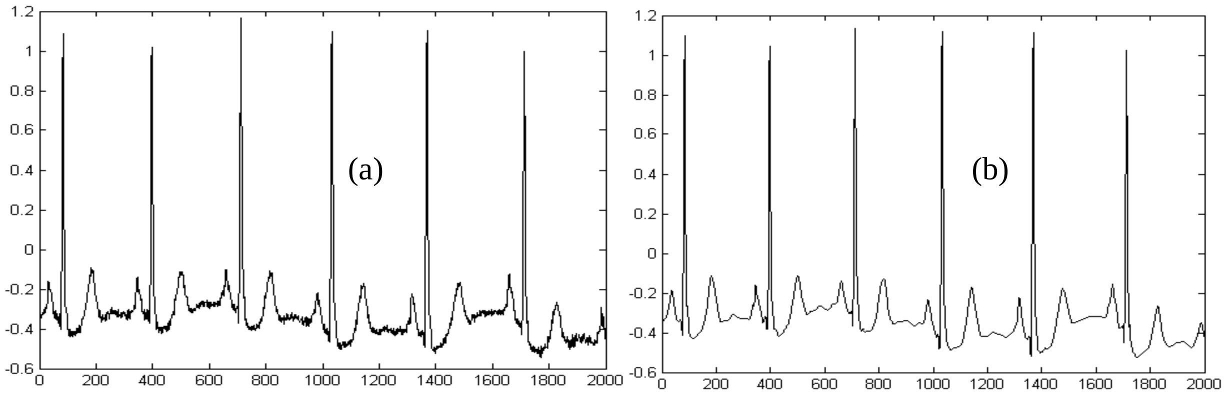

Figure 2. (a) Original Signal Record-101 (b) Reconstructed Signal Record-101

C. Comparison with Other Methods

The compression results obtained with the proposed algorithm for record 117 are listed in Table3. The corresponding results for other methods (Djohan et al., 1995), (Hilton, 1997), (Al-Shrouf et al., 2003) are also listed for comparison. 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 (Djohan et al., 1995), (Hilton, 1997), (Al-Shrouf et al., 2003), records 117 of the database. 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 et al., 2003)	117	5.3	11.6:1
(Djohan et al., 1995)	117	3.9	8:1
(Hilton, 1997)	117	2.6	8:1
Proposed	117	2.5	14.1:1

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 best compression methods in ECG compression.

CONCLUSION

The compression algorithm can be used for most one dimensional non-stationary signals. Storage and transmission limitations have made ECG data compression an important feature for most ECG computerized systems. The proposed compression algorithm compacts as much of the signal energy into as few coefficients as possible. The performance parameters of the compression technique using the applied thresholding technique are measured and a compression ratio of 14.1 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. The proposed method yields to good results in comparison with other previously developed WT based compression methods. It provides improved performance in terms of computational efficiency and compression rate where the clinically significant features in the reconstructed ECG signal are preserved.

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