ELSEVIER
Medical Engineering & Physics 23 (2001) 127–134
Medical Engineering & Physics
www.elsevier.com/locate/medengphy

Compression of ECG signals by optimized quantization of discrete cosine transform coefficients

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Received 22 November 2000; received in revised form 28 February 2001; accepted 15 March 2001

Abstract

This paper presents an ECG compressor based on optimized quantization of Discrete Cosine Transform (DCT) coefficients. The ECG to be compressed is partitioned in blocks of fixed size, and each DCT block is quantized using a quantization vector and a threshold vector that are specifically defined for each signal. These vectors are defined, via Lagrange multipliers, so that the estimated entropy is minimized for a given distortion in the reconstructed signal. The optimization method presented in this paper is an adaptation for ECG of a technique previously used for image compression. In the last step of the compressor here proposed, the quantized coefficients are coded by an arithmetic coder. The **Percent Root-Mean-Square Difference** (PRD) was adopted as a measure of the distortion introduced by the compressor. To assess the performance of the proposed compressor, 2-minute sections of all 96 records of the MIT-BIH Arrhythmia Database were compressed at different PRD values, and the corresponding compression ratios were computed. We also present traces of test signals before and after the compression/decompression process. The results show that the proposed method achieves good compression ratios (CR) with excellent reconstruction quality. An average CR of 9.3:1 is achieved for PRD equal to 2.5%. Experiments with ECG records used in other results from the literature revealed that the proposed method compares favorably with various classical and state-of-the-art ECG compressors. © 2001 IPEM. Published by Elsevier Science Ltd. All rights reserved.

Keywords: Electrocardiogram; Digital signal processing; Data compression; Discrete cosine transform; Quantization

1. Introduction

The extensive utilization of digital ECG produces large amounts of data. Efficient compression techniques are thus required to reduce the amount of data to be recorded or transmitted. Several ECG compression methods have been developed during the last 30 years, and average compression ratios (CR) ranging approximately from 2:1 up to 50:1 have been reported [1,2]. Almost none of the reported techniques permit perfect reconstruction of the original signal. For this reason, these methods are called *lossy compressors*. In spite of great efforts to automatically define the quality of the reconstructed signal, there is still no automatic way to assure that the distortions will not affect some clinically important features of the ECG. For this reason, lossy ECG compression must be employed with care.

The distortion resulting from the ECG processing is frequently measured by the Percent Root-Mean-Square Difference (PRD) [3]. Let $x[n]$ and $\tilde{x}[n]$, $n=0, 1,..., N-1$, represent the values, in mV, of the samples of the original and reconstructed signal, respectively. Then, the PRD is most commonly defined as

$$\mathrm{PRD}=\sqrt{\frac{\sum_{n=0}^{N-1}(x[n]-\tilde{x}[n])^2}{\sum_{n=0}^{N-1}(x[n])^2}}\times 100\% \qquad (1)$$

As this measure is very sensitive to the DC level of

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1350-4533/01/$20.00
PII: S1350-4533(01)00030-3

the original signal, a second definition of the PRD that overcomes this problem is sometimes used:

$$PRD2=\sqrt{\frac{\sum_{n=0}^{N-1}(x[n]-\tilde{x}[n])^2}{\sum_{n=0}^{N-1}(x[n]-\bar{x})^2}}\times 100\% \tag{2}$$

where

$$\bar{x}=\frac{1}{N}\sum_{n=0}^{N-1}x[n] \tag{3}$$

Despite their widely accepted use as distortion measures, PRD and PRD2 do not indicate precisely the quality of the reconstruction [4]. In other words, a low value of these measures does not guarantee total preservation of the essential features of the original record and the decompressed signal has also to be evaluated by visual inspection. Recently, a new ECG distortion measure, called Weighted Diagnostic Distortion (WDD), has been introduced [5]. WDD, which is based on PQRST diagnostic features, seems well correlated with cardiologists' perception, but it is expensive to calculate [4].

Precise comparison of different compression methods is a difficult task, because the results depend heavily on some properties of the signal used, as sampling frequency, resolution, noise level and morphology. Koski [6] has shown that increasing the sampling frequency makes it easier to get higher CR's, while increasing the number of bits per sample makes this task more difficult. As an illustration of how the noise level and signal morphology affect the results, the application of a technique based on the discrete cosine transform (DCT) [7] over 34 signals from the MIT/BIH Arrhythmia Database [8] resulted in a minimum CR of 2.8:1 and a maximum CR of 28.9:1. All signals were sampled at 360 Hz, with 11 bits per sample, and the PRD was fixed at 5%.

All studies on ECG compression show that there is a compromise between CR and distortion [9]. Considering, for example, the Mean-Shape VQ compressor with entropy coding [2], the average CR goes from 13.1:1, with a PRD of 4.1%, up to 50.5:1, with a PRD equal to 20.3%. As a second example, the method based on 2-D DCT of aligned beats [10] achieved a CR equal to 4:1 with an average PRD of 2,7%, and a CR equal to 48:1 with an average PRD of 15.8%. These results indicate the difficulties of achieving a good CR while keeping a low PRD.

In this work we propose a new ECG compression method based on the optimized quantization of Discrete Cosine Transform coefficients. The following sections describe the main features of DCT-based compression and the proposed method.

2. DCT-based compressors

Generally, in transform-based ECG compression methods, an invertible orthogonal transformation is applied to the signal, and one tries to reduce the redundancy present in the new representation. Due to their decorrelation and energy compaction properties and to the existence of efficient algorithms to compute them, Cosine [11] and Wavelet [12] transforms have been widely investigated for data compression. The DCT, for example, has been used for ECG [7,10,13,14], image [11,15,16], video [11], and audio [11] compression.

There are normally 4 general steps in a DCT-based compression of a data sequence **x**:

1. Partition of **x** in N_b consecutive blocks $\mathbf{b}_i$, i =0, 1,..., N_b-1, each one with L_b samples;
2. DCT computation for each block;
3. Quantization of the DCT coefficients;
4. Lossless encoding of the quantized DCT coefficients.

Increasing the block size increases the CR and the DCT computing time. Various results show, however, that increasing the block size above a certain point results in a very modest CR gain, while the processing time significantly increases [10,17].

The type II DCT (DCT-II) [11] is commonly used for data compression due to its greater capacity to concentrate the signal energy in few transform coefficients. Let $b_i[n]$, n =0, 1,..., L_b-1, represent the L_b values in block $\mathbf{b}_i$; the one-dimensional DCT-II of this block generates a transformed block $\mathbf{B}_i$ constituted by a sequence of L_b coefficients $B_i[m]$, m =0, 1,..., L_b-1, given by:

$$B_i[m]=\left(\frac{2}{L_b}\right)^{1/2}c_m\sum_{n=0}^{L_b-1}b_i[n]\cos\left[\frac{(2n+1)m\pi}{2L_b}\right], \tag{4}$$

$$m=0,1,\ldots,L_b-1$$

where c_m =1 for $1\leq m\leq L_b-1$ and $c_0=(1/2)^{1/2}$.

The DCT can be seen as a one-to-one mapping for N-point vectors between the time and the frequency domains [16]. The coefficient $B_i[0]$, which is directly related to the average value of the time-domain block, is often called the *DC coefficient*, and the remaining coefficients of a block are called *AC coefficients*.

Given $\mathbf{B}_i$, $\mathbf{b}_i$ can be recovered by applying the inverse DCT-II:

$$b_i[n]=\left(\frac{2}{L_b}\right)^{1/2}\sum_{m=0}^{L_b-1}c_mB_i[m]\cos\left[\frac{(2n+1)m\pi}{2L_b}\right], \tag{5}$$

$$n=0,1,\ldots,L_b-1$$

To quantize $\mathbf{B}_i$, one can use a *quantization vector*, **q**. Each element $q[n]$, n =0, 1,..., L_b-1, of **q** is a positive integer in a specified interval and represents the quantization step size for the coefficient $B_i[n]$. The elements $\hat{B}_i[n]$ of the quantized DCT block $\hat{\mathbf{B}}_i$ are obtained by the following operation:

$$\hat{B}_i[n]=B_i[n]//q[n], \quad n=0,1,...,L_b-1 \qquad i=0,1,...,N_b-1 \tag{6}$$

where // represents division followed by rounding to the nearest integer.

In a work about image compression, Ratnakar [15] showed that it is possible to achieve a considerable gain in the CR, for a fixed distortion, by using thresholding. If $t[n]$, $n=0, 1,..., L_b-1$ are the elements of the *threshold vector*, $\mathbf{t}$, the elements of $\hat{\mathbf{B}}_i$ are now given by:

$$\hat{B}_i[n]=\begin{cases}0, & \text{if } |B_i[n]|<t[n]\\ B_i[n]//q[n], & \text{otherwise}\end{cases} \qquad n=0,1,\ldots,L_b-1 \qquad i=0,1,\ldots,N_b-1 \tag{7}$$

With or without thresholding, the dequantization, performed during the decompression process to find an approximation to the original coefficients, consists simply in the multiplication of each quantized coefficient by the correspondent component of $\mathbf{q}$.

For most DCT-based compressors, the quantization is the only lossy operation involved. The definition of $\mathbf{q}$ and $\mathbf{t}$ has a strong impact in CR and distortion [15]. A low quality quantization can lead to low compression ratios associated with high distortions. The intrinsic difficulties to define $\mathbf{q}$ and $\mathbf{t}$, though, have led to the utilization of very simple quantization strategies in the DCT-based ECG compressors reported in the literature.

Ahmed et al. [13], for example, uses a unique threshold value t_0 for all coefficients. Coefficients with estimated variances less than t_0 are quantized to zero. All elements of the quantization vector are equal to 1. Varying t_0 controls the CR and the distortion.

The CAB/2-D DCT [10] uses a unique quantization step size for all coefficients. This value is defined to minimize the squared mean error between the original and the reconstructed signal, for a given CR, under the condition of having the same quantization step size for all coefficients. As pointed out by Lee and Buckley [10], the good resulting compression ratios are principally due to a 2-D approach, that simultaneously explores the correlation between consecutive samples and consecutive beats of the signal, rather than to the quantization strategy.

Poel [7] uses a $\mathbf{q}$ vector whose components are values from a line segment. The value of $q[0]$ is fixed at 1 and the next values grow linearly up to the value of $q[L_b-1]$. Varying the inclination of the line segment controls the CR and the distortion.

The lossless encoding of the quantized DCT coefficients generally involves run-length encoding, because the quantization normally generates many null values, followed by an entropy encoder [10].

The present work describes a method to define $\mathbf{q}$ and $\mathbf{t}$ in a way that minimizes the estimated entropy of the quantized coefficients for a given distortion, and uses these optimized vectors as the basis for an ECG compressor. The main goal is to demonstrate the possibility of attaining good compression ratios by using a carefully defined quantization strategy, along with a simple coding scheme.

3. Description of the proposed method

For a given signal, let $H(\mathbf{q}, \mathbf{t})$ be the zero-order entropy of all DCT coefficients quantized by using $\mathbf{q}$ and $\mathbf{t}$, and $D(\mathbf{q}, \mathbf{t})$ a measure of the distortion introduced in the ECG signal by the quantization. The proposed optimization problem can then be stated in two ways:

1. For a given $H(\mathbf{q}, \mathbf{t})$, determine $\mathbf{q}$ and $\mathbf{t}$ in a way that minimizes $D(\mathbf{q}, \mathbf{t})$.
2. For a given $D(\mathbf{q}, \mathbf{t})$, determine $\mathbf{q}$ and $\mathbf{t}$ in a way that minimizes $H(\mathbf{q}, \mathbf{t})$.

A solution to this problem applied in image compression has been proposed by Ratnakar [15]. The minimization method described in this paper is an adaptation, for ECG signals, of the same steps presented by Ratnakar.

Optimization can be achieved by minimizing the Lagrangian $J = H(\mathbf{q}, \mathbf{t}) + \lambda D(\mathbf{q}, \mathbf{t})$ for a given value of the Lagrange multiplier λ [15]. The value of λ that leads to the desired $H(\mathbf{q}, \mathbf{t})$ or $D(\mathbf{q}, \mathbf{t})$, within a given tolerance, can be efficiently found by using the bisection method [18].

For fast DCT calculation, the block size used will be a power of 2. Lee and Buckley [10] tested block sizes from 4×4 to 64×64. Their results indicate that 4×4 blocks perform poorly, and that coding gains start to saturate around size 32×32 or 64×64. Based on these experiments, we chose a block size of 64, with good results. The elements of $\mathbf{q}$ are integer values in the range 1 to 64, based on tests that revealed that no values greater than 64 would improve the optimization; each element $t[m]$ of $\mathbf{t}$ takes values from $q[m]/2$ to 64, with 0.5 increments [15]. Using these values, if we consider only the $\mathbf{q}$ vector, the problem could be solved by exhaustive search by trying each one of the $64^{64}=2^{384}$ different values of $\mathbf{q}$. The process described in the next paragraphs allows reducing the complexity of the problem to practical levels. It should be noted that the entire records to be compressed are used in the determination of optimal $\mathbf{q}$ and $\mathbf{t}$ vectors.

For the optimization procedure, we use the mean square error as the distortion measure $D(\mathbf{q}, \mathbf{t})$. Since the DCT is an orthonormal transform, $D(\mathbf{q}, \mathbf{t})$ can be calculated from the distortions introduced in the DCT coefficients [15]. This eliminates the need to apply the inverse DCT to the dequantized coefficients in order to measure the distortion in the time-domain. Thus, the mean squared error introduced by the quantization can be calculated as:

$$D(\mathbf{q},\mathbf{t})=\frac{1}{L_b N_b}\sum_{i=0}^{N_b-1}\sum_{n=0}^{L_b-1}(B_i[n]-q[n]\hat{B}_i[n])^2 \quad (8)$$

Notice that the mean square error due to the quantization of coefficient number k of all blocks, which will be called $D_k(q[k], t[k])$, is given by

$$D_k(q[k],t[k])=\frac{1}{N_b}\sum_{i=0}^{N_b-1}(B_i[k]-q[k]\hat{B}_i[k])^2 \quad (9)$$

we can write Eq. (8) as

$$D(\mathbf{q},\mathbf{t})=\frac{1}{L_b}\sum_{n=0}^{L_b-1}D_n(q[n],t[n]) \quad (10)$$

Consider now that the coefficient number k of the quantized blocks assumes value v in $n_k(v)$ of the N_b blocks. Then the entropy $H_k(q[k], t[k])$ of the coefficient number k measured over all quantized DCT blocks is given by

$$H_k(q[k],t[k])=-\sum_{v}p_k(v)\log_2 p_k(v) \quad (11)$$

where $p_k(v) = n_k(v)/N_b$.

To estimate the entropy of all quantized coefficients we use the following simplified model [15]:

$$H(\mathbf{q},\mathbf{t})=\frac{1}{L_b}\sum_{n=0}^{L-1}H_n(q[n],t[n]) \quad (12)$$

In the experimental results presented by Ratnakar [15], the error between the estimated and the real entropy was normally below 0.02 bits/symbol, which indicates the precision of the model.

With the possibility to calculate $D(\mathbf{q}, \mathbf{t})$ and $H(\mathbf{q}, \mathbf{t})$ as the mean of the distortion and of the entropy of each coefficient, the minimization of J reduces to the minimization of

$$J_n=H_n(q[n],t[n])+\lambda D_n(q[n],t[n]), n=0,1,\ldots L_b-1 \quad (13)$$

In other words, the minimization can be independently done for each coefficient. With this simplification, if L_b =64 samples and the elements of $\mathbf{q}$ are integer values in the range 1 to 64, only $64*64=2^{12}$ of the 64^{64} possible values of $\mathbf{q}$ need to be analyzed in the minimization procedure. This complexity reduction combined with the use of histograms, incremental calculations and other techniques [15], allow performing an efficient search for the optimum $\mathbf{q}$ and $\mathbf{t}$ vectors.

After defining the optimum $\mathbf{q}$ and $\mathbf{t}$ for a given signal, the compressor closely follows the steps of general DCT-based compressors already described:

1. Partition of $\mathbf{x}$ in N_b consecutive blocks $\mathbf{b}_i$, i =0, 1,..., N_b-1, each one with 64 samples
2. Computation of the DCT blocks, $\mathbf{B}_i$, i =0, 1,..., N_b-1
3. Quantization of $\mathbf{B}_i$, i =0, 1,..., N_b-1, using the optimum $\mathbf{q}$ and $\mathbf{t}$
4. Lossless encoding of the quantized DCT coefficients

As a result of quantization, each quantized block $\hat{\mathbf{B}}_i$ normally ends in a large run of null coefficients. The lossless encoding step exploits this fact as follows. Let k_i be the number of the coefficient that precedes the last run of null coefficients in $\hat{\mathbf{B}}_i$. This final run is eliminated and the difference between k_i and k_{i-1} is put in the beginning of $\hat{\mathbf{B}}_i$. For $\hat{\mathbf{B}}_0$, k_0 is directly encoded. To explore the good correlation that exists between DC coefficients of adjacent blocks, the quantized DC coefficient of $\hat{\mathbf{B}}_i$ is encoded as $\hat{B}_i[0]-\hat{B}_{i-1}[0]$. Again, $\hat{B}_0[0]$ is directly encoded. In the resulting sequence S, each value within the range [−127, 126] is represented as a single byte value. A value $v \leq -128$ is represented as a sequence of c bytes with value equal to −128, where c is the greatest integer such that $128c \leq |v|$, followed by a byte with value equal to $v+128c$. Similarly, a value $v \geq 127$ is represented as a sequence of c bytes with value equal to 127, where c is the greatest integer such that $127c \leq v$, followed by a byte with value equal to $v-127c$. For example, the value −300 would be represented as (−128, −128, −44). In practice, for ECG signals, almost all symbol values in S lie within the range [−127, 126]. The sequence S is finally coded by an order-0 semi-adaptive arithmetic encoder [19].

The decompression involves the following steps:

1. Lossless decoding of S
2. Dequantization of $\hat{\mathrm{B}}_i$, i =0, 1,..., N_b-1, using the optimum $\mathbf{q}$
3. Computation of the inverse DCT of the dequantized blocks
4. Concatenation of the time-domain blocks produced in step 3.

To allow arithmetic decoding and dequantization, the optimum $\mathbf{q}$ and a "count table" containing the number of occurrences of each value in S must be included in the compressed file. With L_b =64 samples and $q[n]$ limited to integer values between 1 and 64, the optimum $\mathbf{q}$ occupies 64*6=384 bits in the compressed file. Using two bytes to represent the number of occurrences of the symbols in *S*, the count table occupies 256*16=1572 bits. Thus the optimum **q** and the count table take only 1956 bits in the compressed file.

4. Results

To experimentally assess the performance of the proposed method, we used the first two minutes of both channels of the 48 records of the MIT-BIH Arrhythmia Database. These ECG signals were sampled at 360 Hz with 11 bits/sample. Our test set is therefore composed of 96 signals, with 43 200 samples each. We determined the optimum **q** and **t** vectors for each test signal and for target PRD levels of 1.5%, 2.0%, 2.5% and 3.0%, within a 0.04 tolerance. In all cases, the real PRD resulting from the compression/decompression process was within the desired range.

Table 1
Average, maximum and minimum CR obtained with the proposed method for the test signals. The standard deviations are also shown

PRD (%)	Average CR	Standard Dev.	Maximum CR	Minimum CR
1.5	6.2	3.2	17.3	2.5
2.0	7.9	4.2	26.2	2.6
2.5	9.3	4.9	29.4	2.8
3.0	10.9	5.8	35.3	3.1

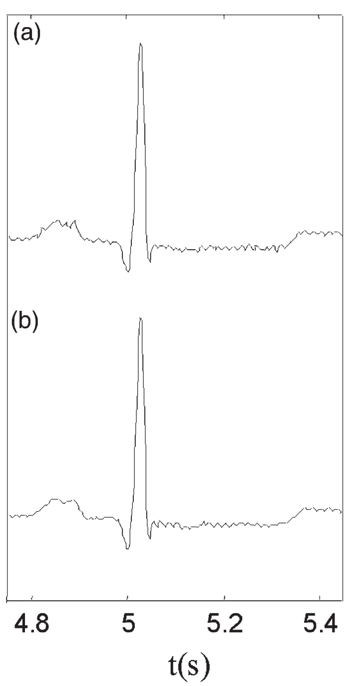

Fig. 1. Detail of (a) record 100/MLII and (b) reconstructed signal for PRD =2.5%, CR =9.1

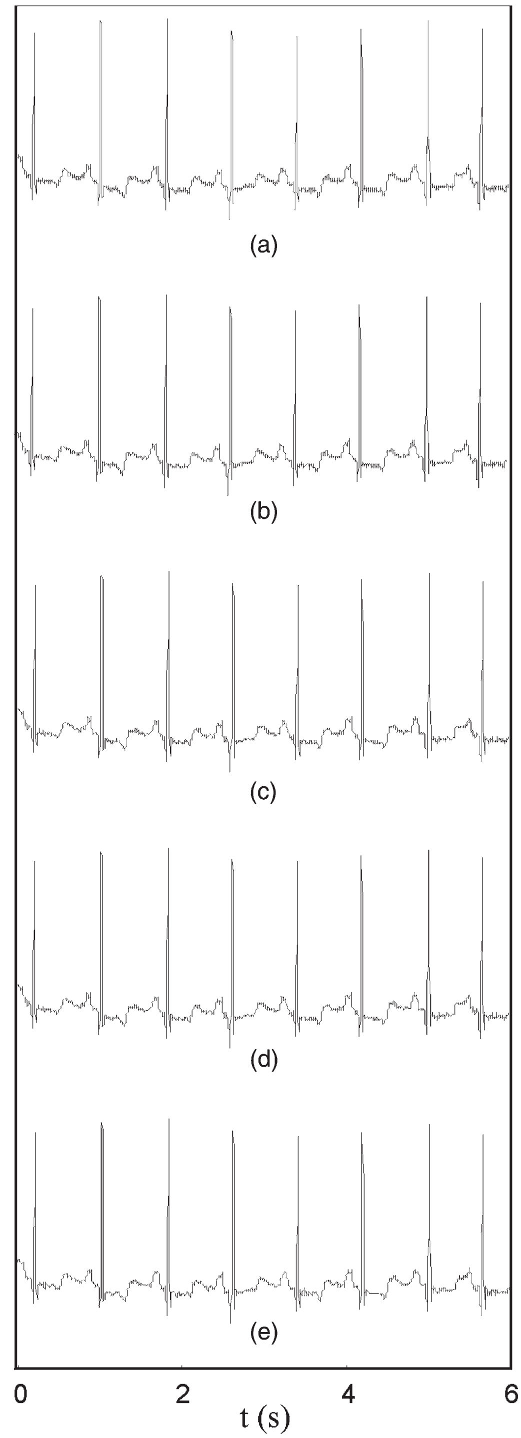

Fig. 2. (a) Part of record 100/MLII, and reconstructed signal for (b) PRD =1.5%, CR =5.9; (c) PRD =2.0%, CR =7.6; (d) PRD =2.5%, CR =9.1; and (e) PRD =3.0%, CR =10.2.

After determining the optimum **q** and **t** vectors, the signals were compressed and the compression ratios were computed. Table 1 shows the average, maximum and minimum CR and the standard deviation obtained for the complete test set for each PRD value.

Fig. 1 presents a single cycle of record 100/MLII from

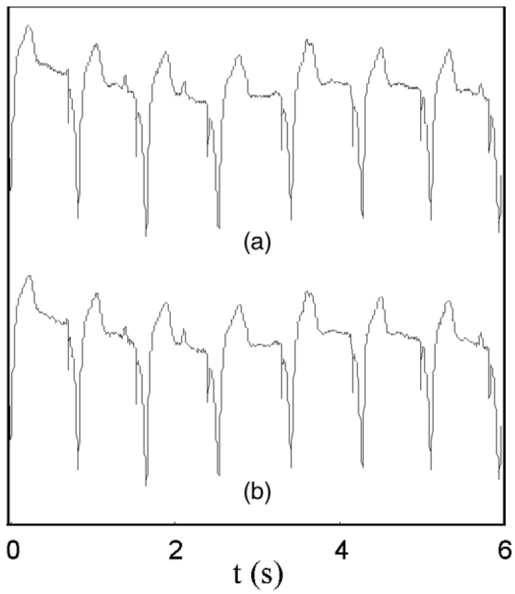

Fig. 3. (a) Part of record 107/V1, and (b) reconstructed signal for PRD =2.5%, CR =8.0.

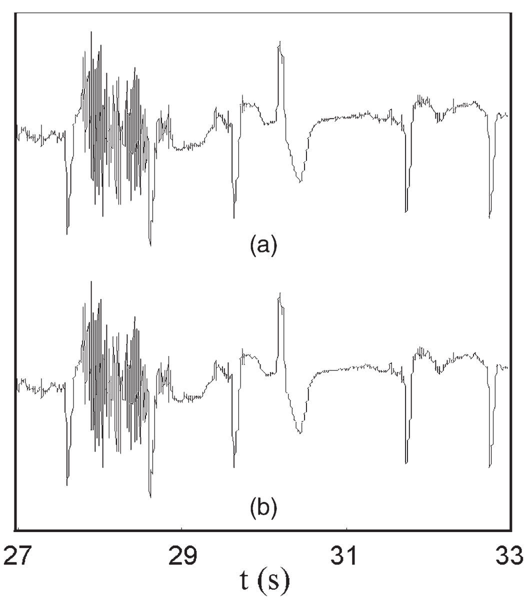

Fig. 4. (a) Part of record 108/V1, and (b) reconstructed signal for PRD =2.5%, CR =9.8.

the MIT/BIH Arrhythmia Database, and the reconstructed signal for PRD equal to 2.5% and CR equal to 9.1:1, allowing detailed analysis of the distortions in important regions of the signal. Figs. 2–5 allow visual assessment of the quality of the reconstruction at various distortion levels for some larger sections of ECG traces with different characteristics. Fig. 2 presents the first 6 seconds of record 100/MLII from the MIT/BIH Arrhythmia Database, and the reconstructed signal for PRD equal to 1.5%, 2.0%, 2.5% and 3.0%. Figs. 3–5 show 6-s sections from records 107/V1, 108/V1 and 109/MLII

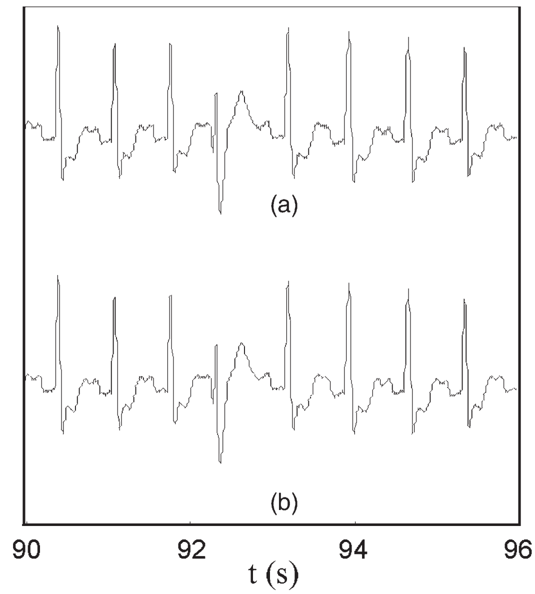

Fig. 5. (a) Part of record 109/MLII, and (b) reconstructed signal for PRD =2.5%, CR =8.8.

respectively, and the reconstructed signals for PRD equal to 2.5%. These traces indicate an excellent preservation of QRS complexes and of all important signal features. Fig. 4 shows the performance of the compressor in the presence of severe noise.

For a given target PRD, our implementation of the proposed method took approximately 25 min to compress the whole test set, which represents 192 min of signal. The processing was performed on a 400 MHz AMD K6-III running Windows 98. This time includes the reading of the signals from the hard disk, the definition of the optimum **q** and **t** vectors for the target PRD, and the compression of the signals. It must be emphasized that our implementation does not employ most of the available techniques [15] to efficiently search optimum **q** and **t**.

In order to compare the performance of the method here proposed with other ECG compressors, we selected from the literature a number of results that report CR and PRD (or PRD2) obtained with precisely defined sections of records from the MIT/BIH Arrhythmia Database. We then ran our compressor over the same test signals and compared the PRD values for the same CR, within a 0.04 tolerance. Since we emphasize low distortion, we kept CR $\leq$20.0:1 in all cases. Table 2 summarizes the results. Numbers marked by a [a] are PRD2 values. In the last column of Table 2, a brief description of the size and variety of the test set used is presented. The results reported in the literature were in some cases obtained after changing the sampling rate or the number of bits per sample of the ECG signal. As this kind of preprocessing significantly affects CR, we also altered the signals accordingly. In these situations, the modified

Table 2
Compression and distortion comparison between variousECG compressors from literature and the proposed compressor

From literature		Proposed compressor PRD (%)	CR	Test set
Compressor	PRD(%)			
Sub-band compressor/ F16B FIR filter [20]	2.8[a]	2.5[a]	7.3	14.22-s of 6 records
AZTEC [5]	15.5[a]	3.3[a]	6.9	1-min of each channel of 18 records
Scan-along polygonal approximation [5]	9.6[a]	3.3[a]	6.9	1-min of each channel of 18 records
Long term prediction [5]	7.3[a]	3.3[a]	6.9	1-min of each channel of 18 records
Analysis by synthesis compressor/ASEC$_{PRD}$ [5]	4.0[a]	3.3[a]	6.9	1-min of each channel of 18 records
Adaptive optimized quantization of wavelet coefficients [21]	6.8	6.5	12.5	10-min of the upper channel of record 200
Mean-shape vector quantizer [2]	4.1	3.4	13.1	1-min of each channel of all records (500Hz)
Adaptive differential pulse coded modulation [10]	2.6	1.2	4.0	10-min of each channel of 2 records
	6.9	1.9	6.0	
1-D DCT [10]	4.1	1.2	4.0	10-min of each channel of 2 records (250Hz, 12 bits/sample)
	7.5	1.9	6.0	
	15.1	4.4	12.0	
Cut and align beats approach with 2-D DCT [10]	2.5	1.2	4.0	10-min of each channel of 2 records
	3.5	1.9	6.0	
	6.1	4.4	12.0	
Gold washing adaptive vector quantization/wavelet transform [22]	3.3[a]	1.6[a]	4.6	15-min of the upper channel of 4 records
	6.3[a]	4.0[a]	9.4	
	8.2[a]	5.7[a]	12.4	
Wavelet compression by set partitioning in hierarchical trees [23]	1.2	1.2	4.0	10-min of each channel of 11 records
	3.0	2.9	10.0	
	6.5	6.3	20.0	
Peak selection and DCT [24]	3.0	1.4	5.3	1-min of 1 channel of 6 records

[a] PRD2.

sample rate or number of bits per sample is indicated in parentheses after the description of the test set.

5. Discussion and conclusions

In this paper, we presented an effective ECG compression technique based on a carefully designed quantization strategy applied before only to image compression. Our results show that this quantization strategy was successfully adapted for ECG signals.

Results obtained by running the compressor over the first two minutes of both channels of the 48 records of the MIT-BIH Arrhythmia Database show that the proposed method is capable of achieving good average CR values with low distortion. We presented 6-seconds sections of four records for visual assessment of the quality of the reconstruction at various distortion levels. These traces present different characteristics and indicate an excellent preservation of all important signal features.

We also performed tests to directly compare our method with classical and recently published ECG compressors. Our method compared favorably with the other compressors, producing considerably smaller PRD (or PRD2) for a given CR. Only in some instances the differences were not large. This is the case, for example, when comparing our method with the sub-band compressor with F16B FIR filter of Johnston [20] and with the adaptive optimized quantization of the wavelet coefficients [21]. Moreover, for three different CR levels, the corresponding PRD values obtained with our algorithm were virtually identical to those obtained with the wavelet ECG compressor by set partitioning in hierarchical trees (ECG-SPIHT), which is an adaptation for ECG signals of SPIHT [25], considered the premier image compression algorithm [23].

Since a very simple coding scheme was employed in the last step of our algorithm, it is clear that the good CR×PRD compromise achieved is mainly due to the careful quantization strategy adopted. There is much room for improvement in the lossless stage. For example, run-length encoding of zero sequences and a more elaborate entropy coder should improve CR for a given PRD. In fact, some preliminary tests are already being performed in the lossless stage of the compressor, with excellent results.

The strategy adopted here defines a unique instance of the **q** and **t** vectors for each signal. However, the frequency content of blocks containing QRS complexes, for example, is much different from the frequency content of the other blocks. Thus, significant gains in CR could probably be achieved by using different optimized **q** and **t** vectors for different blocks.

Increasing block size increases CR for a given distortion, but also increases processing time; thus, the decision about block size is fundamentally open. We observed a good compromise between processing time, compression ratio and distortion with a block size of 64.

The superiority of our method and of CAB/2-D DCT with respect to 1-D DCT [10] suggests that combining the quantization strategy used here with a 2D approach similar to that used in CAB/2-D DCT might result in good compression gains.

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