Compression of Polysomnographic Signals Using the Discrete Cosine Transform and Deadzone Optimal Quantization

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***Abstract*—Data compression techniques for electrocardiographic and electroencephalographic exams have been widely reported in the literature over the last decades; but, there are no papers offering a unique solution for all biological signals typically present in polysomnographic records. Aiming to fill this gap, the present work proposes a method of lossy compression for polysomnographic signals based on optimal quantization of the coefficients obtained from the discrete cosine transform. The potentially grave distortions generated by the information loss are controlled by a compression parameter that may be configured to reach the desired Normalized Percent Root-mean-square Difference generating the optimum quantization vector with a minimization of the Lagrange parameter. The quantized signal is sent to a prediction by partial matching compressor, which works as the entropy coder of this compression strategy. The method was tested using the signals in the Polysomnographic database created by the Massachusetts Institute of Technology and Boston's Beth Israel Hospital, achieving compression ratios between 2.16:1 and 67.48:1 with distortion values between 1.0% and 4.0%.**

Keywords–data compression; telemedicine; polysomnographic signals; lossy compression; discrete cosine transform.

I. INTRODUCTION

The technological advances in data transmission have turned the ability to communicate into one of the foundations of the contemporary society. Access to broadband Internet, despite recent technological advances, still remains as a service which is accessible to few people, especially in third world countries. Likewise, a large amount of hard disk space may represent a great cost for applications with either personal or commercial purposes. One way to ease these problems is to reduce the need for storage and/or transmission of data, while preserving all or most of the information on the original message.

The methods used in messages to minimize the disk space needed for its storage is the process called data compression, and this special type of data processing is classified into lossy and lossless compression techniques. A lossless compression and decompression process of a signal results in a reconstructed signal with exactly the same information as the original one. A lossy compression technique may produce a fairly accurate approximation of the original signal, depending on the compression techniques and the parameters used in these techniques.

The biological signals are among the various types of signals on which lossy compression techniques may be applied. These signals are often used for either biometrical or diagnostic purposes, requiring a very low amount of errors – or even none – in a reconstructed signal decoded after the application of a lossy compression method. Polysomnographic (PSG) monitoring has been useful to clarify the physiological mechanism to produce sleep related signs or attacks, such as apnea, arrhythmia, hemodynamics changes, and/or myocardial ischemia [1]. Therefore, this kind of exam cant be performed during day time and is usually done in specialized clinics. The disk space needed for the storage of one hour of a PSG channel may be as large as 2.57 MB, if a proper digitalization is used in the process. Some PSGs may contain nine data channels, resulting in a disk space of approximately 23 MB/h. In eight hours, the average sleep duration of a human being, this signal requires a space equivalent to 185 MB. This may not seem much for the storage capacity of modern computers, but it represents a huge scalability problem when the exams need to be stored for the rest of the patients life for health progress evaluation. This large amount of space represents a problem for the design of embedded homecare polygraphs, which can perform most of these exams in the patients house. This problem can be eased with the use of smart lossy data compression techniques over the PSGs, achieving a good Compression Ratio (CR).

There are no works describing a solution for a unified method for compression of PSGs; so, some modern techniques for electrocardiographic (ECG) and electroencephalographic (EEG) compression will be described as follows:

The method proposed by Mukhopadhyay et al. [2] uses a differentiation technique to detect all R-peaks in the ECG signal, allowing the algorithm to apply a differential encoding process to R-peak regions (also called QRS regions). The QRS slices are passed to an algorithm based on a Lossless Compression using Character Encoding (LLCCE), since these parts of the ECG are more important to the signal reconstruction. The rest of the ECG is passed to a sub sampler, which reduces the sampling frequency of the signal by one half. Then non-QRS data are processed by a Lossy Compression using Character Coding Encoding (LCCE) scheme. The non-parameterized compressor was tested using the Physikalisch-Technische Bundesanstalt (PTB) Diagnostic ECG Database and reported a CR value of $23.10 : 1$ with a Percent Root-mean-square Difference (PRD) value of 7.55%.

Ranjeet et al. [3] uses a Cut And Align (CAB) strategy

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to slice the ECG signal and reorganize the blocks in a 2D array, which is passed to a 2D Discrete Wavelet Transform (DWT). The remaining coefficients are encoded using Huffman entropy coding, achieving an average of 65% in compression efficiency with 0.999 correlation score. The tests performed using this near lossless strategy resulted in an optimum 2D array size of $180x20$ samples in the Massachusetts Institute of Technology and Boston's Beth Israel Hospital (MIT-BIH) Arrhythmia Database [4].

The work described by Lai et al. [5] explores the use of the Discrete Cosine Transform (DCT) IV – in contrast to the DCT-II, often used for compression purposes. Initially, the ECG signal is divided into DCT blocks with 64 samples, then a differential coding procedure is applied, feeding a Huffman entropy coder. This non-parameterized strategy achieved an average CR of $5.25:1$ with a PRD of 0.19% and a Normalized Percent Root-mean-square Difference (NPRD) of 2.88% using the MIT-BIH Arrhythmia Database [4].

The method described by Anas et al. [6], similarly to the present work, is a DCT-based compressor. It uses the correlation between the ECG cycles (identified by QRS complexes) to eliminate the redundancy in the data of the records. This ECG compressor has a preprocessing step counting with baseline elimination, an average filter, a high pass filter and a butterworth filter, preparing the record to the compression routine. Then, the ECG is passed to a R-peak detector, the ECG cycles are interpolated to a fixed value $M = 512$, normalized to an interval $[0, 1]$, transformed using the DCT, quantized and encoded. This parameterized method achieved good CRs for low PRD values, but only the results obtained by the compression of three records from the MIT-BIH Arrhythmia Database [4] were published.

Srinivasan et al. [7] propose a multichannel near-lossless EEG compression algorithm based on image and volumetric coding. The algorithm arrange multichannel EEG signal in the form 2D image or 3D volume, then apply either a 2D or 3D DWT to exploit simultaneously both spatial and temporal correlation in a single procedure. The proposed algorithm achieved a compression ratio of 6.63 with PRD of 9.21% for a quantizer step-size equals to ten in one of the datasets used.

The fact that no work in the literature describes a compression technique for all the PSGs is responsible for the non-existence of a standard distortion measure for the lossy compression of these signals. However, there is a large amount of papers describing lossy and lossless compression methods for electrocardiographic signals. The lossy compressors often use the PRD as an objective evaluation of the distortion present in the decoded signal. The PRD is defined as:

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

This measure is very sensitive to the baseline of the original signal. A second definition for the PRD, the NPRD, which overcomes this problem, is described by Batista et al. [8] as:

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

where $\overline{x}$ is given for:

$$\overline{x} = \frac{1}{N} \sum_{n=0}^{N-1} x\left[n\right] \qquad (3)$$

The NPRD, however, is still not the ideal distortion measure for biological signals, as it does not consider the different characteristics present in each record. This criterion only provides an objective approximation for the amount of errors in the reconstructed signal.

This paper is organized as follows: Section I presents an overview about the PSG data volume problem, the method we propose to solve it and the quality metrics we used. Section II gives an overview about PSG signals. Section III explains the basis of DCT-based lossy compressors. Section IV explains the proposed compression method. Section V shows the results obtained by the test application. Section VI describes the conclusions obtained after the analysis of the results and some possible applications for the proposed method.

II. Polysomnographic Signals

The PSGs may include several types of signals, including both well-known signals as electrocardiograms and electroencephalograms; and signals with more specific purposes, as electrooculograms (EOG), stroke volume (SV) and oxygen saturation records (SO2). The signals included and discarded from the exams are determined by the health condition the physician wants to analyze and the patients health state.

The large diversity of behavior among the PSGs is responsible for the lack of unified compression solutions for all signals described in the biological data compression literature. While some signals are periodical, as ECG, blood pressure (BP) and respiration (Resp) signals, other signals are almost completely chaotic, as electromyographic (EMG), EOG and EEG records. Some works take advantage of the periods in ECG records to achieve greater CR values and other works cover only EEG signals, but none of them was tested in all PSGs.

The work described by Ichimaru and Moody [1] presents a standardized physiological PSG database format, including an amount of 18 signals, with duration ranging from two to seven hours. The PSGs were digitalized with 250 Hz sampling frequency and a 12 bits/sample quantization. The so called MIT-BIH Polysomnographic Database became the standard test corpus for the PSG processing applications. An image of the samples of a signal in the MIT-BIH Polysomnographic Database is shown in Fig. 1.

III. DCT-based Compressors

Among the several domain transformations applicable to digital signals, the DCT [9] and the DWT [10] have been

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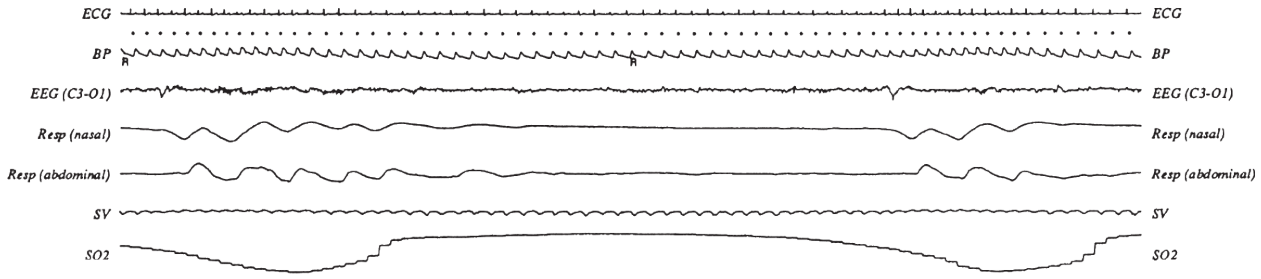

Figure 1. Full disclosure of the polysomography data. Including ECG, BP, EEG, Resp, SV and SO2 records. Adapted from [1].

widely used in lossy compressors due to their energy compaction properties. Fast implementations of both transforms in both 1 and 2 dimensions have been described in the data compression literature over the last decades. The DCT – the most popular one – is used in many encoding formats, including ECG encoders [11][12][13][14]; video encoders [15][16]; still image encoders [17]; and audio encoders [9]. As described by Batista et al. [8], there are four steps often used for the creation of DCT-based encoders to compress 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 [12][18]. The DCT-II is widely used in lossy data compressors and it is the closest unitary transform approximation for the optimal Karhunen-Love Transform (KLT) [9]. 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:

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

where $c_m = 1$ for $1 \leq m \leq L_b - 1$ and $c_0 = \sqrt{\left(\frac{1}{2}\right)}$.

The DCT can be seen as a one-to-one mapping for N-point vectors between the time and the frequency domains [17]. 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 applying the inverse DCT-II:

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

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:

$$\hat{B}_i[n] = B_i[n] // q[n] \tag{6}$$

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

Ratnakar [19] 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, **t**, the elements of $\hat{\mathbf{B}}_i$ are now given by:

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

The dequantization, performed during the decompression process to find an approximation to the original coefficients, consists simply in a multiplication of each quantized coefficient by the correspondent component of **q**. For most DCT-based compressors, the quantization is the only lossy operation involved. The definition of **q** and **t** has a strong impact in CR and distortion [19].

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 [12] 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. As pointed out by Lee and Buckley [12], the good resulting compression ratios are principally due to a 2D approach, which simultaneously explores the correlation between consecutive samples and consecutive beats of the signal, rather than to the quantization strategy.

The work presented by Poel [11] uses a **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.

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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 [12].

The present work describes a method to define **q** and **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 a PSG compressor. The main goal is to demonstrate the possibility of attaining good compression ratios by using a carefully defined quantization strategy.

IV. Description of the Proposed Method

The measure used for the calculation of the distortion after the compression was the NPRD due to the baseline variation among the PSG signals. Some PSGs, such as the respiratory (Resp) signals, may have a very high baseline value, allowing the error amount of the common PRD to grow a lot for a low PRD value. The NPRD unifies the computation of the distortion to a single measure, without the need of a baseline elimination preprocess.

To reduce the long-term storage problem created by exams involving PSGs in small and medium sized clinics, the purposed technique was created. This unified solution was tested in the four main PSG signals: ECG, EEG, BP and Resp. The method works as a parameterized compressor, defining the optimum **q** and **t** vectors for the codification of each channel in the signal. An optimization for the choice of the **q** and **t** parameters was made using the minimization of the Lagrange multiplier for each DCT coefficient, similarly to the work presented in Ratnakar [19], which proposed a solution to the optimum quantization of images. The Lagrangian minimization allows the compressor to perform an independent optimization for each coefficient independently. The number of decoding iterations using exhaustive search methods N_{exa} – as shown in (8) – is then optimized to a much lower value N_{opt}.

$$N_{exa} = {Q_{max}}^B + {T_{max}}^B \tag{8}$$

Lee and Buckley [12] tested the use of a 2D DCT with block sizes from $4x4$ to $64x64$, narrowing the tests only to powers of 2. These tests resulted in a saturation of the coding gain with block sizes around $32x32$ and $64x64$ samples. Based on the experiments presented in [12] and the ones performed by Batista et al. [8], we used block sizes containing 16, 32 and 64 samples in the tests.

For a given signal, let $H(\mathbf{q}, \mathbf{t})$ be the zero-order entropy of all DCT coefficients quantized by using **t** and **t**, and $D(\mathbf{q}, \mathbf{t})$ a measure of the distortion introduced in the PSG signal by the quantization. The proposed optimization problem can then be given by the statement: for a given $D(\mathbf{q}, \mathbf{t})$, determine **q** and **t** in a way that minimizes $H(\mathbf{q}, \mathbf{t})$.

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 [19]. 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 [20]. The Lagrangian minimization allows the compressor to set a maximum number of decoding operations empirically predefined by tests of the method on the signals. The number N_{opt} was set to the value 17 in the test application, but this number may vary according to the type of signal, its digitalization parameters and its statistic distribution.

Empirical tests showed that NPRD values lower than or equal to 3.0% required Q_{max} and T_{max} values lower than 128, thus, this was the maximum value the elements of the QT vectors could reach for these distortions. For NPRD values higher than 3.0%, the maximum values for the QT elements were set to 256. Therefore, for NPRD values higher than 3.0% using 64 samples DCT blocks, N_{exa} would assume the value $2.68x10^{154}$. 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 to calculate the optimal **q** and **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 [19]. 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:

$$D(\mathbf{q}, \mathbf{t}) = \frac{\sum_{i=0}^{N_b-1} \left[\sum_{n=0}^{L_b-1} \left(B_i[n] - q[n] \hat{B}_i[n] \right)^2 \right]}{L_b N_b} \tag{9}$$

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:

$$D_k(q[k], t[k]) = \frac{1}{N_b} \sum_{i=0}^{N_b-1} \left(B_i[k] - q[k] \hat{B}_i[k] \right)^2 \tag{10}$$

Thus, we can write (9) as:

$$D(\mathbf{q}, \mathbf{t}) = \frac{\sum_{n=0}^{L_b-1} D_n(q[n], t[n])^2}{L_b N_b} \tag{11}$$

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:

$$D_k(q[k], t[k]) = -\sum_v [p_k(v) \log_2(p_k(v))] \tag{12}$$

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

To estimate the entropy of all quantized coefficients we use the following simplified model [19]:

$$H(\mathbf{q}, \mathbf{t}) = \frac{1}{L_b} \sum_{n=0}^{L-1} [H_n(q[n], t[n])] \tag{13}$$

In the experimental results presented by Ratnakar [19], 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:

$$J_n = H_n\left(q\left[n\right],t\left[n\right]\right) + \lambda D_n\left(q\left[n\right],t\left[n\right]\right), \quad n = 0,1,...,L_b-1 \tag{14}$$

In other words, the minimization can be done independently 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 256, only $64 * 256 = 2^{14}$ of the 64^{256} 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 [19], 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. A scheme representing graphically the compressors steps is shown in Fig. 2.

The dead-zone quantization step of the encoding process normally generates a large amount of subsequent null frequency samples, mostly in the high frequency AC coefficients. This characteristic of the quantized signal allows the compressor use an efficient lossless entropy coding technique, such as a Golomb coding [21] or a Huffman coding [22]. The proposed method does not aim to achieve a hardware implementation compression model; so, for validation purposes, we used a more efficient lossless coding algorithm, the Prediction by Partial Matching (PPM) [23]. The optimal entropy coding of the DC coefficients – which tend to assume higher values than the AC coefficients – was also decisive to the choosing of the PPM. The PPM creates a generic statistic distribution model in the coding process, so the high values in the DC coefficients are not a problem for the optimal coding of the signal.

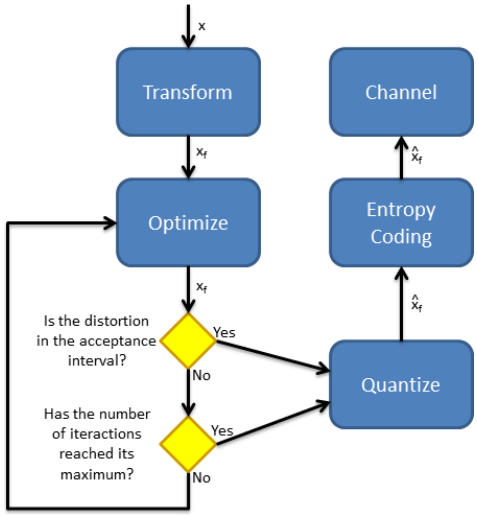

Figure 2. Scheme showing the processing steps used by the proposed compressor.

The decompressor, as in many other lossy codecs, is a simple subset of the compressor. It is composed by three simple steps, recreating an approximation to the original signal by applying the inverse encoding operations in an inverse order. The first decompression stage is to run a decoding operation, retrieving the domain frequency quantized signal $\hat{\mathbf{x}}_f$ from the channel it was stored by the compressor. Then a dequantization operation is applied, creating the approximation to the signal still composed by frequency domain coefficients $\tilde{\mathbf{x}}_f$. At last, an inverse DCT transform is run over the DCT blocks in the $\tilde{\mathbf{x}}_f$ signal, generating the approximated time domain original signal $\tilde{\mathbf{x}}$. Fig. 3 presents an overview of the decompression scheme.

V. Results and Discussion

Table I and Table II show, respectively, the CR results from compression– using NPRD values among 1.0% and 4.0%, and with DCT block sizes of 16, 32 and 64 samples – of ECG and EEG signals, which showed the best visual reconstruction qualities. Table III and Table IV show the findings for BP and Resp signals, respectively, which obtained good results with certain combinations of parameters, although they have tolerated NPRD values lower than the other signals to approximately the same level of visual distortion. The thresholding effect of these signals proved to be stronger than the other PSGs, explaining the high CR values obtained, since most of the information to be encoded by the PPM in the entropy coding stage is concentrated on the DC levels of the blocks generated by the DCT signals.

In more chaotic signals, which also have a larger amount of noise, such as ECGs, the best results of optimum compression were obtained with DCT blocks of smaller size, as seen in Fig. 4(a). This result is reversed in the case of more linear and less noisy PSGs, such as BP and Resp signals, which is shown in Fig. 4(b).

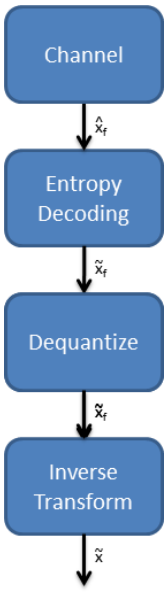

Figure 3. Scheme showing the processing steps used by the proposed decompressor.

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TABLE I. CR RESULTS FOR NPRD VALUES BETWEEN 1.0% AND 4.0% AND DCT BLOCK SIZES OF 16, 32 AND 64 SAMPLES FOR ECG SIGNALS.

DCT block size	NPRD						
	1.0%	**1.5%**	**2.0%**	**2.5%**	**3.0%**	**3.5%**	**4.0%**
16	2.52401	3.05967	3.49161	4.0208	4.8165	5.22089	5.98384
32	2.43439	2.8334	3.23771	3.84271	4.38118	4.83237	5.22027
64	2.26796	2.64573	3.02288	3.43338	3.84632	4.09859	4.72272

TABLE II. CR RESULTS FOR NPRD VALUES BETWEEN 1.0% AND 4.0% AND DCT BLOCK SIZES OF 16, 32 AND 64 SAMPLES FOR EEG SIGNALS.

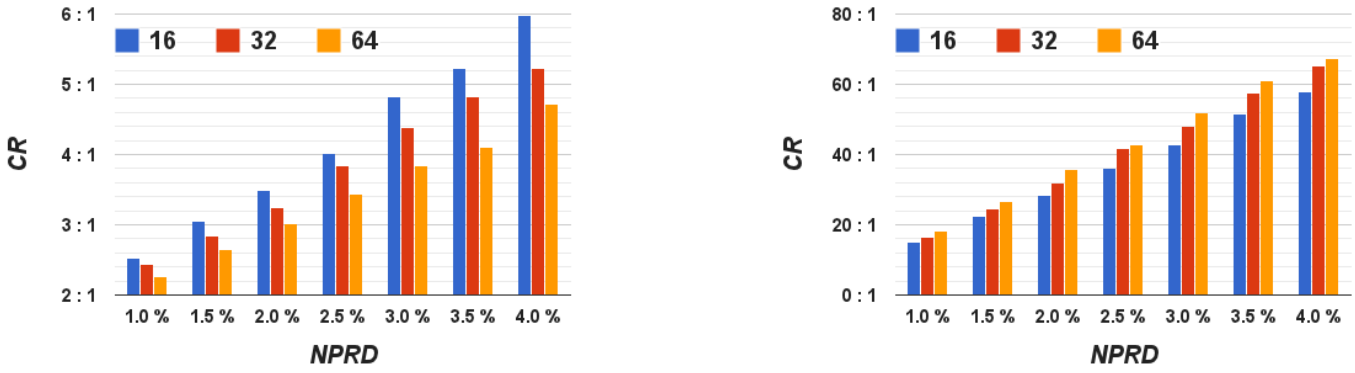
DCT block size	NPRD						
	1.0%	**1.5%**	**2.0%**	**2.5%**	**3.0%**	**3.5%**	**4.0%**
16	2.16316	2.49929	2.78552	3.05686	3.34842	3.6387	3.9742
32	2.18337	2.53933	2.82184	3.13717	3.43413	3.79547	4.18758
64	2.21229	2.55054	2.8828	3.09125	3.53912	3.75921	4.07101

TABLE III. CR RESULTS FOR NPRD VALUES BETWEEN 1.0% AND 4.0% AND DCT BLOCK SIZES OF 16, 32 AND 64 SAMPLES FOR BP SIGNALS.

DCT block size	NPRD						
	1.0%	**1.5%**	**2.0%**	**2.5%**	**3.0%**	**3.5%**	**4.0%**
16	7.05813	9.83612	12.5254	15.0561	16.9096	18.5575	20.813
32	7.6318	11.0152	13.7244	16.2092	18.397	20.6467	22.6501
64	8.31705	11.9357	14.9918	17.6552	20.0764	22.2745	24.4644

TABLE IV. CR RESULTS FOR NPRD VALUES BETWEEN 1.0% AND 4.0% AND DCT BLOCK SIZES OF 16, 32 AND 64 SAMPLES FOR RESP SIGNALS.

DCT block size	NPRD						
	1.0%	**1.5%**	**2.0%**	**2.5%**	**3.0%**	**3.5%**	**4.0%**
16	14.9775	22.3109	28.533	36.1156	42.9171	51.4388	57.9435
32	16.4825	24.6164	32.0925	41.7645	47.9586	57.3724	65.4241
64	18.2037	26.8057	35.7891	42.893	52.0199	61.0977	67.4799



(a) (b)

Figure 4. NPRD x CR graphic showing the evolution of the CRs for different block sizes in (a) ECG signals. (b) Resp signals.

As seen in Fig. 5, the reconstruction of the ECG signals achieved very good results, even for higher NPRD values, as 4.0%. This means that this value can be increased even more without grave reconstruction errors. EEG signals, although much more chaotic, had a reconstruction quality close to the ECGs for the same values of NPRD, as seen in Fig. 6. As expected, these signals obtained the lowest CRs among the PSGs due to the large amount of information present in their samples.

The reconstruction of BP signals, exemplified by Fig. 7, showed a strong thresholding effect for signal reconstruction with NPRD values higher than 3.0%. The compression of these signals resulted in high CRs, even for tests with lower NPRD values, allowing compressions with milder distortions to be applied and still result in acceptable CR values. Some kinds of medical exams require only the basic shape of the signal to be stored, so, depending on the purpose of the exam, the thresholding effect can be accepted for BP signals, achieving higher CRs.

In Resp signals (see Fig. 8) like the BPs, the effect of thresholding was strong enough in tests with higher NPRD values, but the CR obtained with the compression of these PSGs is the best among all PSGs thanks to its continuity and to a small amount of noise present in the samples. This allows the application of lighter quantization, still achieving good CR values.

Compression using the Lagrangian minimization to determine the optimal parameters did not behave well with signals

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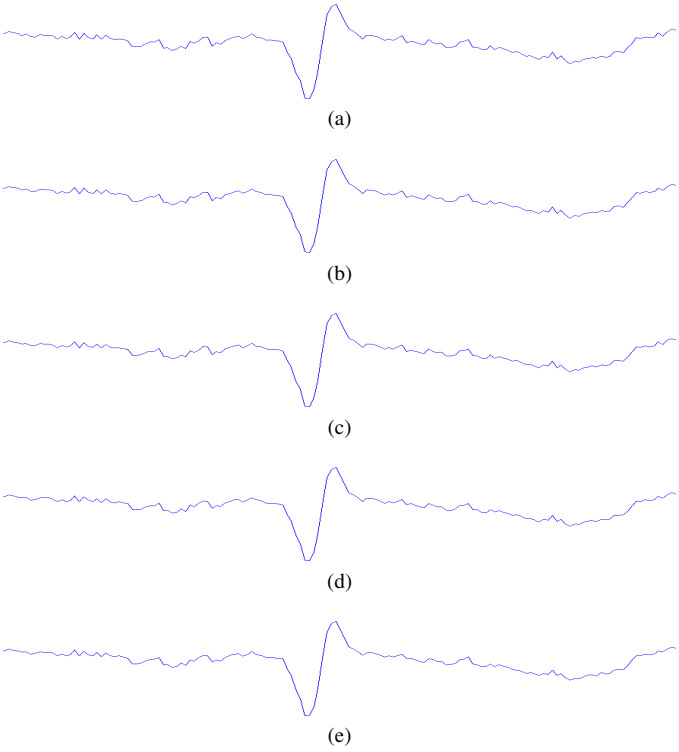

Figure 5. Slice of the ECG channel of the file slp37.dat of the MIT-BIH Polysomnographic Database (a) original. (b) reconstructed with a NPRD of 1.0%. (c) reconstructed with a NPRD of 2.0%. (d) reconstructed with a NPRD of 3.0%. (e) reconstructed with a NPRD of 4.0%.

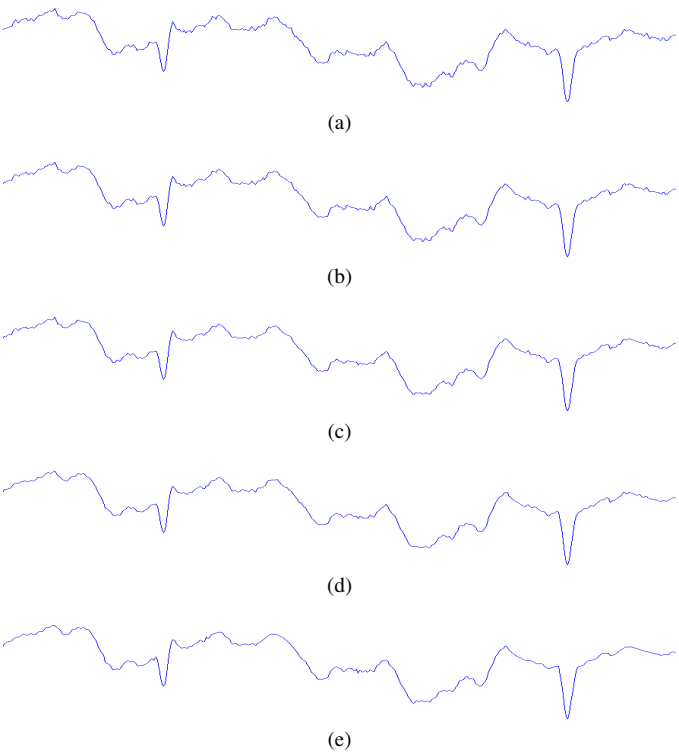

Figure 6. Slice of the EEG channel of the file slp01a.dat of the MIT-BIH Polysomnographic Database (a) original. (b) reconstructed with a NPRD of 1.0%. (c) reconstructed with a NPRD of 2.0%. (d) reconstructed with a NPRD of 3.0%. (e) reconstructed with a NPRD of 4.0%.

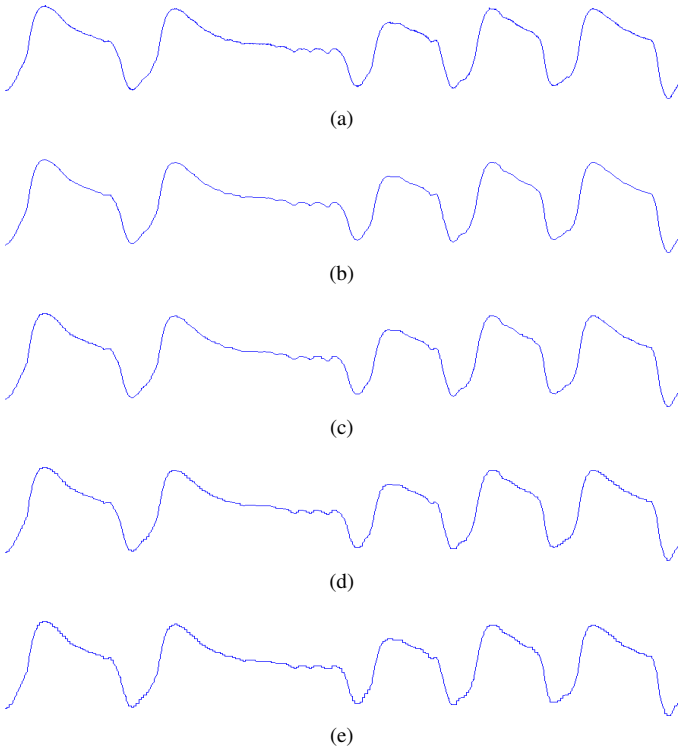

Figure 7. Slice of the BP channel of the file slp16.dat of the MIT-BIH Polysomnographic Database (a) original. (b) reconstructed with a NPRD of 1.0%. (c) reconstructed with a NPRD of 2.0%. (d) reconstructed with a NPRD of 3.0%. (e) reconstructed with a NPRD of 4.0%.

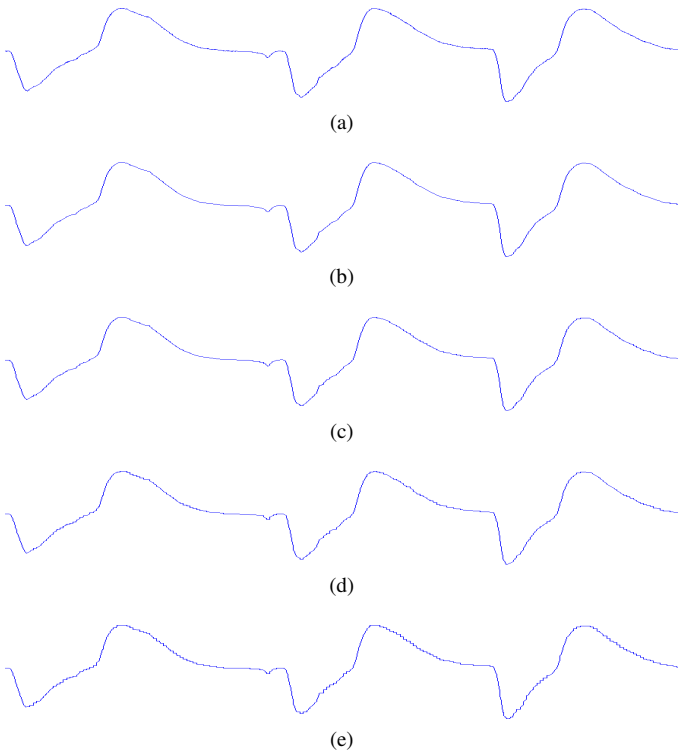

Figure 8. Slice of the Resp channel of the file slp16.dat of the MIT-BIH Polysomnographic Database (a) original. (b) reconstructed with a NPRD of 1.0%. (c) reconstructed with a NPRD of 2.0%. (d) reconstructed with a NPRD of 3.0%. (e) reconstructed with a NPRD of 4.0%.

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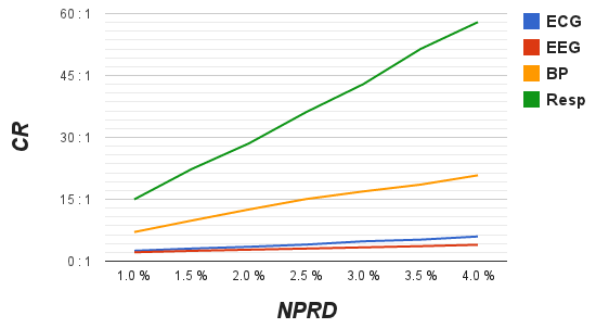
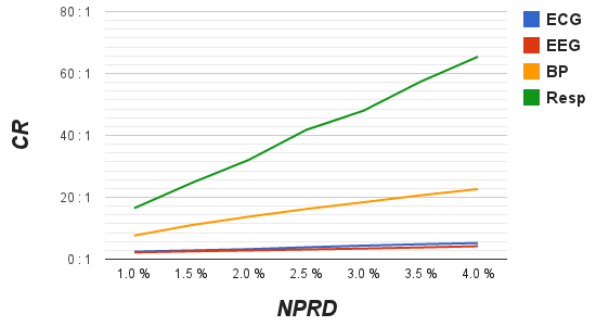
with a highly uneven statistical distribution. The large number of samples with values outside the normal range interferes with the calculation of the NPRD, since this measure is inversely proportional to the standard deviation, which is highly affected by values outside a certain range near the baseline of the signal. A high standard deviation allows a higher value for the numerator of the equation – the Root Mean Square Error (RMSE) – to achieve the same NPRD, which implies a very large amount of visual errors.

Although in most signals the DCT blocks with 64 samples obtained the best CR, these blocks also feature a worse visual reconstruction quality, if compared to PSGs with the same NPRD values compressed using blocks with 16 or 32 samples. The CR evolution graphics for different NPRD values in ECG, EEG, BP and Resp records are seen in Fig. 9.



(a)



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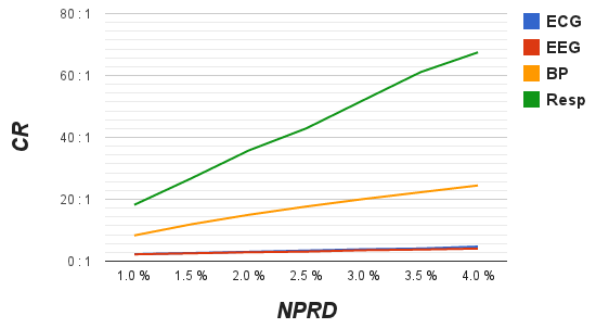


(c)

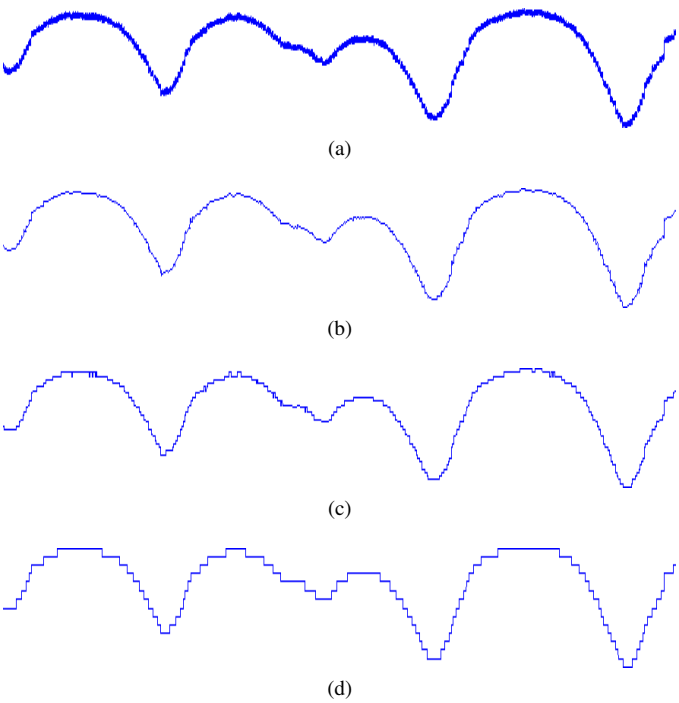
Figure 9. CR evolution for ECG, EEG, BP and Resp signals according to different NPRD values in DCT blocks of (a) 16 samples. (b) 32 samples. (c) 64 samples.

All PSGs showed basically the same CR evolution in different blocks sizes. In some signals it is noticeable a greater change in the CR values for higher NPRDs, what may be attributed to the amount of redundant information, the amount of noise present in the original signal and the amplitude of the samples.

The optimal quantization tends to eliminate signal noise, leaving its baseline more visible and removing the temporal redundancy present in their samples. Some signals – as Resp and BPs – suffer from a faster saturation in the visual quality because of their higher standard deviation.

Depending on the amount of noise that can be accepted in the ECG and EEG signals, an increase of desired NPRD passed to the compressor presents a good CR performance at the cost of low noise, reaching $5.98 : 1$ and $4.18 : 1$, respectively, for NPRD values of 4.0%. The CR values of ECGs came close to the compression obtained by [8], if a visual analysis of the reconstructed signals is performed. A more detailed comparison with studies involving the compression of ECGs and EEGs is hampered by the use of databases where the digitalization process was done differently than [1], hindering the comparison using objective distortion measures. The frequent use of the PRD – and not the NPRD – for the calculation of the errors of the reconstructed signal is also a factor that complicates a comparison with other papers.

Fig. 10 shows the effect of sensor defects in a SO2 signal. These PSG channels – along with the EMGs, EOGs and SV – were not considered by the tests because of the large amount of errors present in their capture processes and the low number of signals containing channels of these records in [1].



(a)

(b)

(c)

(d)

Figure 10. Slice of the SO2 channel of the file slp67x.dat of the MIT-BIH Polysomnographic Database affected by errors (a) original. (b) reconstructed with a NPRD of 1.0%. (c) reconstructed with a NPRD of 2.0%. (d) reconstructed with a NPRD of 4.0%.

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The runtime of the compressor varied according to the length of the signal, since the database has no fixed length for the signals. The larger signals considered for this papers test routines – with six hours and four data channels – were compressed in less than 30 minutes. This result enables the adoption of the proposed method for practical cases, since the compression method took less than a sixth of the length of the signals to compress the data. Since most polysomnographic exams are performed during night time, clinics can use a fraction of the daytime to compress the PSG records captured during the previous night.

Embedded mobile systems for PSG exams with less processing power than conventional computers may divide the captured recordings into slices, allowing the execution of the record to run at the same time as the compress algorithm for the previous data section. This may result in cheaper homecare PSG capture devices, bringing more comfort to the patients.

VI. Conclusion

Technological advances in the processing and storage capacities of personal computers and the price reduction of the biological signal sensors allowed the popularization of medical exams using polysomnographic signals. There was an increase in the data volume generated by these types of exams, although no compression techniques covering the codification of all PSGs have been reported in the data compression literature.

We presented a lossy parameterized compression method for PSGs, prioritizing the reconstruction quality of the compressed signals. A Lagrangian minimization was used to drastically reduce the computational complexity for the choice of the optimal dead-zone quantization vectors. The amount of errors allowed in the reconstruction of the PSGs may vary according to their diagnostic purpose, presetting the compressor in order to tolerate lower or higher objective distortions.

For low NPRD values the compressor achieved different results, depending on the entropy of the PSG. The best CRs were reached in EEG signals, which varied between $2.16:1$ and $4.17:1$. In ECG signals, on the other hand, CR ranged between $2.26:1$ and $5.98:1$. The BP signals were compressed with CRs in interval of $7.05:1$ and $24.06:1$. The highest compression ratios were obtained by the method in Resp signals, with values in the range of $14.97:1$ and $67.47:1$. However, low objectives distortion metrics do not imply in a good visual quality of signals reconstruction.

Empirical tests validated the presented codification technique, which achieved a small runtime in comparison to the length of the original signals. The simplicity of the method may be a motivation for the development of both hardware implemented solutions and desktop applications.

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