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Electroencephalographic Compression Based on Modulated Filter Banks and Wavelet Transform

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Abstract— **Due to the large volume of information generated in an electroencephalographic (EEG) study, compression is needed for storage, processing or transmission for analysis. In this paper we evaluate and compare two lossy compression techniques applied to EEG signals. It compares the performance of compression schemes with decomposition by filter banks or wavelet Packets transformation, seeking the best value for compression, best quality and more efficient real time implementation. Due to specific properties of EEG signals, we propose a quantization stage adapted to the dynamic range of each band, looking for higher quality. The results show that the compressor with filter bank performs better than transform methods. Quantization adapted to the dynamic range significantly enhances the quality.**

I. Introduction

EEG signals represent the electrical activity of the brain captured on the scalp surface. These signals are important for studying many brain conditions including sleep disorders, epilepsy, Alzheimer's disease, etc. Diagnosis is primarily based on visual inspection and interpretation of signal waveforms. Nowadays, as part of the development of computer and telecommunication technologies, EEG signals are commonly stored, transmitted and/or automatically processed. Telemedicine has become more and more important, especially in rural areas, emergency medicine or as a second choice in health care [1]. In these “digital” contexts, the technical quality of EEG recordings must be satisfactory for purposes of clinical use. Typical sampling conditions use 250 Hz and 12 bits or higher [2], and a large number of recording channels during long periods of time are not uncommon. Under these circumstances, data reduction can become very desirable or even mandatory.

Data reduction techniques are generally classified into two categories: lossless and lossy. Lossless compression always achieves an exact replica of the original signal. Lossy compression, on the other hand, can only achieve some level of similarity with the original signal and then, signal quality assessment becomes an important performance issue.

Research on signal compression has generated a number of coding techniques tailored to reduce the amount of EEG data [3,4]. Lossless methods haven't proved to be very efficient in terms of data reduction capabilities [3-5]. Alternatively, lossy compression methods typically offer higher compression ratios at a cost of some signal degradation [6-9]. Apart from obtaining good compression ratios with imperceptible degradation of signal quality, data reduction techniques should also hold low computational costs; particularly if they are going to be implemented on portable devices.

Many EEG rhythms and waveforms have known and localized spectral content and then, subband decomposition becomes an attractive approach for signal coding [10]. This paper proposes a lossy compression method that uses Nearly-Perfect Reconstruction Cosine-Modulated Filter Banks (N-PR CMFB) [11] to decompose the EEG signal into clinically significant subbands, quantizes the subband samples and run length encodes the stream of quantized samples. The proposed method attains high compression ratios and guaranties adequate quality of the reconstructed signals for medical diagnosis. The N-PR CMFB leads to low computational complexity as there exist fast and efficient implementations of the analysis and synthesis filter banks [12]. This paper also presents a direct comparison of the proposed algorithm with another multirate approach based on wavelet packet decomposition. Finally we adapt the quantization phase of the method to the dynamic range of each subband, as a means to further improve reconstructed signal quality.

II. Performance metrics

The ultimate purpose of any compression algorithm is to reduce the number of bits to represent the original signal, which is assessed by means of the compression ratio (CR).

$$CR = \frac{\textit{number of bits of original signal}}{\textit{number of bits of compressed signal}}. \tag{1}$$

To reach this goal, compression methods introduce certain, sometimes undesirable, effects such as the increase of computational complexity, processing delays, and coding noise or distortion. Percent root-mean square difference

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(PRD) is commonly used to quantify the effect of distortion.

Let $x[n]$ and $\hat{x}[n]$ be the original and reconstructed signals respectively, N the length of the window over which the metrics are calculated, an expression for PRD which signal is given by:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x[n]-\hat{x}[n])^2}{\sum_{n=1}^{N}(x[n])^2}} \cdot 100. \quad (2)$$

This parameter is a global indicator of the quality of the reconstructed signal and allows inferring how closely the algorithm has preserved the original signal waveforms. Lower values indicate closer preservation of signal waveforms.

III. Cosine Modulated Filter Bank

In this paper we use N-PR CMFB as a method to split segments of the input signal into several, clinically meaningful, uniformly distributed frequency bands. The interest for these filter banks is based on its efficient implementation capacity through polyphase structures that significantly reduce computational complexity [11].

An N-PR CMFB is a subclass of modulated M-channel maximally decimated filter bank whose structure is shown in Fig. 1.

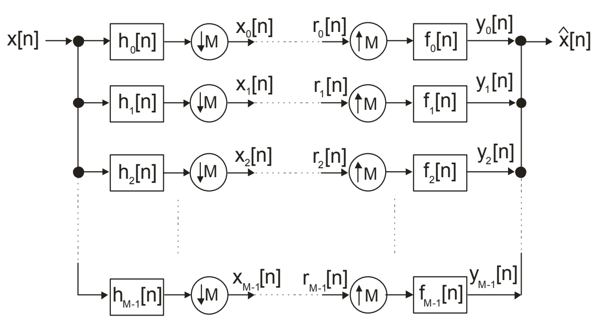

Fig. 1. Schematic of a filter bank of M channels.

The design of all the analysis $h_k[n]$ and synthesis $f_k[n]$ filters, $0 \le n \le (L-1)$, $0 \le k \le (M-1)$, is based on cosine modulated versions of a low-pass prototype filter $p[n]$ as follows:

$$h_k[n] = 2p[n]\cos\left[(2k+1)\frac{\pi}{2M}\left(n-\frac{L}{2}\right)+(-1)^k\frac{\pi}{4}\right],$$

$$f_k[n] = 2p[n]\cos\left[(2k+1)\frac{\pi}{2M}\left(n-\frac{L}{2}\right)-(-1)^k\frac{\pi}{4}\right]. \quad (3)$$

We designed two filter banks with 16 and 32 channels in order to decompose digitally sampled EEG signals, into subbands of 8 or 4 Hz of bandwidth respectively, as most meaningful EEG rhythms and waveforms have disjoint frequency content that lie in an approximately 4Hz-wide bands [10]. We followed the technique proposed in [11] to design the linear-phase prototype lowpass filter $p[n]$.

IV. Wavelet Packets

Wavelet Packets (WP) represent a generalization of the DWT (discrete wavelets transform). Wavelet packet decomposition is commonly implemented by repeated application of a two channel orthonormal filter bank. The result is a complete binary tree as in Fig. 2 with a number of levels that depends on the desired resolution scale.

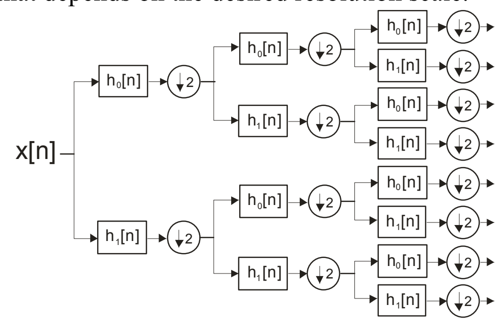

Fig. 2. Complete binary tree of 3 levels to the WP transform.

The binary tree represents a library of bases that can be selected by a process of pruning to efficiently represent the input signal. In this work we have used unpruned trees with 4 and 5 decomposition levels in order to compare WP decomposition with the N-PR CMFB already designed.

V. Compression Scheme Used

The general scheme of our compression method is shown in Fig. 3. The EEG signal is divided into non-overlapped segments $x[n]$ of 2048 samples and the algorithm processes each segment independently. The first stage focuses on signal decorrelation using one of the previously mentioned decomposition methods: namely the N-PR CMFB and WP decompositions.

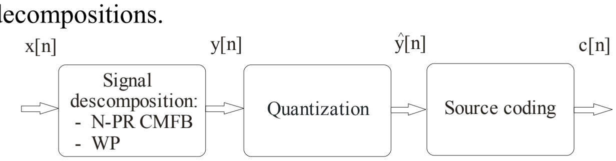

Fig. 3. Compression scheme.

The second stage performs quality driven quantization of subband coefficients $y[n]$ based on thresholding. Thresholds are calculated based on the distortion that can be tolerated on reconstructed signals [12] and distortion is measured using the PRD equation (2). Subband samples that remain after thresholding undergo scalar quantization. We have selected and compared two scalar quantization approaches:

- Uniform scalar quantization using 7 bits that covers the dynamic range of the signal segment.
- Uniform scalar quantization adapted to the dynamic range of each band. The number of bits needed for each subband is calculated based on the dynamic range the corresponding subband.

The last stage uses run length encoding (RLE) to efficiently code the possibly, large number of zero-valued samples output $\hat{y}[n]$ during the thresholding process. Finally $c[n]$ is a coded stream bits.

VI. RESULTS

Our experiments were performed on a comprehensive set of EEG signals extracted from the publicly available MIT-BIH Polysomnographic Database [2]. Sampling conditions in this database use 250Hz sampling frequency and 12 bits per sample resolution.

A. Analysis with N-PR CMFB

In our first experiment we use N-PR CMFB decomposition, thresholding, uniform quantization and RLC. Figure 4 shows the results, in terms of rate distortion curves (CR vs. PRD), when both, the 16 channel and the 32 channel filter banks were used for compressing the EEG signal from the slp01a record of the mentioned database. We varied a target PRD (PRDaim) from 1 and 10 and checked the effect on CR and the actual PRD of the reconstructed signal. Instead of plotting the PRD of the entire signal, we present the mean values and standard deviations (STD) calculated from the PRDs obtained upon reconstruction of signal segments. We can notice that better results are obtained with filter banks of 16 bands. However, the compression performance is far from the one achieved using a similar compression scheme on ECG signals [12]. The main reason for this performance mismatch is that the EEG signal exhibits a more information spread over much of the frequency spectrum [10]. Therefore, thresholding does not always produce a large number of zero-valued samples and prevents the encoding stage based on RLE from achieving a high compression. Another important fact that can be drawn from Fig. 4 is that there exists a lower bound on the expected PRD that can be used.

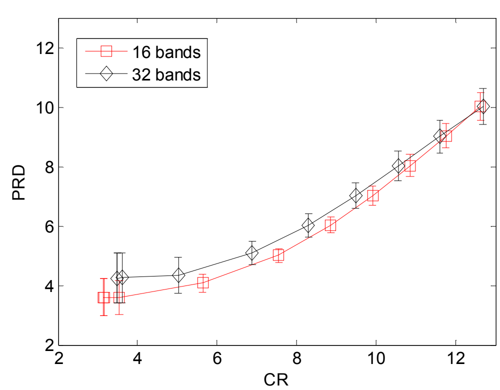

Fig. 4. PRD ± STD vs CR for slp01a signal, with 7-bit uniform quantization, for 16 and 32 bands N-PR CMFB.

This limitation arises mainly because we are employing a coarse quantization scheme that uses 7 bits to represent any subband sample. To a lesser extent, the use of N-PR CMFB filter banks also contributes to coding noise.

B. Analysis with WPs

We ran the same experiment as in section *VI.A* but in this case we used WP decomposition. WP trees were grown to depths 4 and 5 resulting in filter bank structures like those used with N-PR CMFB. Periodic extension was used at segment boundaries. Some wavelet packet bases were evaluated and the discrete Meyer wavelet basis (*dmey*) was chosen as it resulted the one with the fewest number of nonzero coefficients after thresholding was performed with respect to a target PRD.

Figure 5 shows the rate distortion curve generated after applying the compression algorithm with WP decomposition to the EEG signal of the slp01a record from the database. Although the mean values remain very similar to those obtained when N-PR CMFB decomposition was used; deviation from these values were significantly higher.

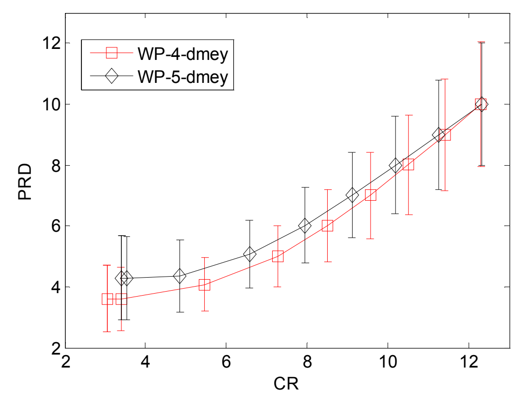

Fig. 5. 7-bit uniform quantization, PRD ± STD vs. CR, for the signal slp01a, 4 and 5 levels WP, *dmey*.

Table I presents explicit numeric performance comparison between the two signal decomposition approaches after compressing the signal with a target PRD (PRDaim) 5% and 10%. It remains clear that results obtained with N-PR CMFB outperformed those obtained when WP decomposition was used, meaning that the distortion of any segment is closer to the distortion constraint we specified.

Table I. Comparative between N-PR CMFB and WP for slp01a signal.

Parameter	*N-PR CMFB 16*		*WP 4 levels*	
PRDaim	5	10	5	10
PRD	5.01	10.03	5.00	10.00
STD	0.23	0.46	1.00	2.06
PRDmax	6.41	11.74	12.12	24.11
CR	7.54	12.62	7.26	12.29

Similar performance to that shown in Table 1 was achieved for other signals of this database. Other reported lossy compression techniques (See [9] and refs. herein), achieve similar performance indicators, but with higher computational demands. Unfortunately, we cannot make a fair and direct comparison with these other techniques as they use different EEG databases and sampling conditions.

C. Quantization adapted to the dynamic range of each band

In our compression scheme, uniform quantization after thresholding can introduce significant errors, mainly when low PRD values are expected. This experiment is carried out with the aim of improving the results obtained above, for PRD values lower than 5 and also to ensure that there will be no significant local errors, as evidenced in the STD and PRDmax. For this purpose, quantization of nonzero coefficients after thresholding is adapted to the dynamic range of each band of the filter bank 16 and 32 channels of the type N-PR CMFB. The number of quantization bits in any subband depended on the dynamic range held by the samples in that subband. We also set upper bounds to the number of quantization bits to check the impact on distortion of this quantization step. Again, the EEG signal from the Slp01a record of the database was selected for comparing compression results. Figure 6 presents compression results when the maximum number of quantization bits was set to 7 bits. If we compare this figure with Figure 4, in which the same uniform quantization was used for all the subbands we observe a more linear behavior for PRD values below 5. Figure 7 shows the simulation results when the maximum number of quantization bits was raised to 8 bits. The use of 8 bits results in higher quality of reconstructed signals but it also has a detrimental effect on CR. In general, this quantization approach results in better reconstructed signal quality at the expense of some decrement of CR.

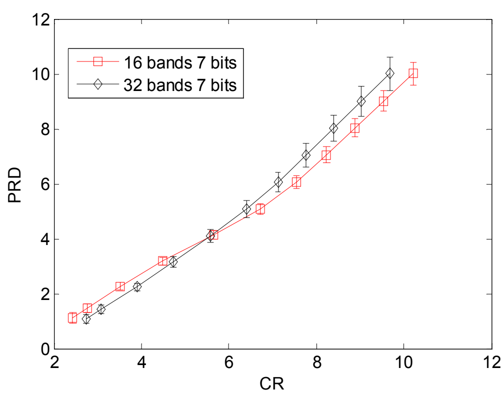

Fig. 6. PRD ± STD vs. CR for slp01a signal, variable quantization in each band with a maximum of 7 bits, with N-PR CMFB to 16 and 32 bands.

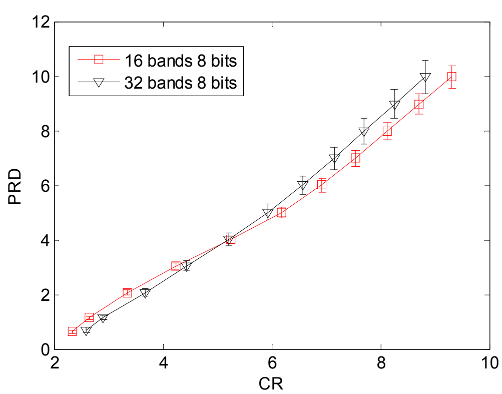

Fig. 7. PRD ± STD vs. CR for slp01a signal, variable quantization in each band with a maximum of 8 bits, with N-PR CMFB to 16 and 32 bands.

Table II shows some interesting values that allow us to select the maximum number of bits in this quantization scheme. These results were obtained without applying any distortion constraint (Threshold = 0) in order to highlight the influence of the adaptive quantization.

Table II. Results for slp01a signal.

Parameter	*N-PR CMFB 16*		*N-PR CMFB 32*	
Quant. bits	7	8	7	8
PRDmin	1.12	0.62	1.09	0.69
STD	0.18	0.07	0.15	0.08
PRDmax	1.94	0.99	1.98	1.21
CR	2.43	2.34	2.65	2.59

Using 8 bit adaptive quantization almost halves distortion performance with little impact on compression ratio.

VII. Conclusion

The results of this work show that the decomposition using filter banks N-PR CMFTB performs better than WP when a uniform quantizer is used. The use of these filter banks are very useful for lossy compression of EEG signals to achieve high compression ratio when high quality is demanded. In this way, waveform morphology of signal may be better guaranteed for diagnosing neurological disease. Quantization based on thresholding introduces error. This effect can be minimized when quantization is adapted to the range values of each band. However, this manner of encoding reduces the compression ratio. Other coding techniques better adapted to the decomposition strategies used, and more suitable criteria for quality assessment must be found, to ensure clinical acceptability of reconstructed waveforms.

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