Data Compression of Natural Signals based on Discrete Wavelet Transform Analysis

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Abstract. In this paper we explore the use of the discrete wavelet transform analysis of an arbitrary signal in order to improve the data compression capability of data coders. Wavelet analysis is widespread used in image codifiers, for example in JPEG2000. The wavelet compression methods are adequate for representing transients, such as percussion sounds in audio, or high-frequency components in two-dimensional images, for example an image of stars on a night sky. The wavelet analysis provides a subband decomposition of any arbitrary signal, and this enables a lossless or a lossy implementation with the same architecture. The signals could range from speech to sounds or music, but the approach is more orientated to other natural signals like arbitrary discrete series, EEG or ECG. Experimental results based on coefficients quantification, show a lossless compression of 2:1 in all kind of signals, and lossy results preserving most of the signal waveform of about 5:1 to 3:1.

Keywords: data compression, source coding, discrete wavelet transform analysis.

1 Introduction

Data compression or source coding techniques try to use the minimum of bits/s to represent information of a source; they could be classified in lossless compression -totally reversible- and lossy compression, allowing better compression rates with some distortion on recomposed signal. Lossless compression schemes usually exploit statistical redundancy and are reversible, so that the original data can be reconstructed [1]; while lossy data compression are usually guided by research on how people perceive the data, and accept some loss of data in order to achieve higher compression. In speech and music coding [2],[3], there are several standards like CELP (used in digital telephony), or the family of MP3 (MPEG 1 layer 3, for audio coding). There are two basic lossy compression schemes: in lossy predictive codecs (i.e. CELP), previous and/or subsequent decoded data are used to predict the current sound sample or image frame [4], the error between the predicted data and the real data, together with any extra information needed to reproduce the prediction, is then quantized and coded; by the other hand, in lossy transform codecs (i.e MP3), samples of picture or sound are taken, chopped into small segments, transformed into a new basis space, and quantized. In some systems the two techniques are combined, with transform codecs being used to compress the error signals generated by the predictive stage. In a second step, the resulting quantized values are then coded, using lossless coders (like run-length or entropy coders like Huffman coder).

In this paper we explore the use of the discrete wavelet transform analysis of an arbitrary signal in order to improve the data compression capability of the first step. Wavelet analysis is widespread used in image codifiers [4],[5], for example in JPEG2000: using a 5/3 wavelet for lossless (reversible) compression and a 9/7 wavelet (Cohen-Daubechies-Feauveau biorthogonal wavelet [6]) for lossy (irreversible) compression.

The wavelet compression methods are adequate for representing transients [5], such as percussion sounds in audio, or high-frequency components in two-dimensional images, for example an image of stars on a night sky. This means that the transient elements of a data signal can be represented by a smaller amount of information than would be the case if some other transform, such as the more widespread discrete cosine transform or the discrete Fourier transform, had been used.

This paper investigates the application of discrete wavelet transforms, specifically the Cohen-Daubechies-Feauveau biorthogonal wavelet [6], for the compression of different kinds of unidimensional signals, like speech, sound, music or others like EEG [7], ECG or discrete series. Preliminary experimental results show a lossless compression of 2:1 in all kind of signals, and lossy results preserving most of the signal waveform of about 5:1 to 3:1. .

2 Discrete Wavelet Transform Analysis

The discrete wavelet transform analysis could be seen as a method for subband or multiresolution analysis of signals. The fast implementation of discrete wavelet transforms is done with a filter bank for the analysis of signals, and the inverse transform is done with a synthesis filter bank (Fig.1) [5]. The first application of this scheme was in speech processing as QMF (Quadrature Mirror Filter) [8] and [9].

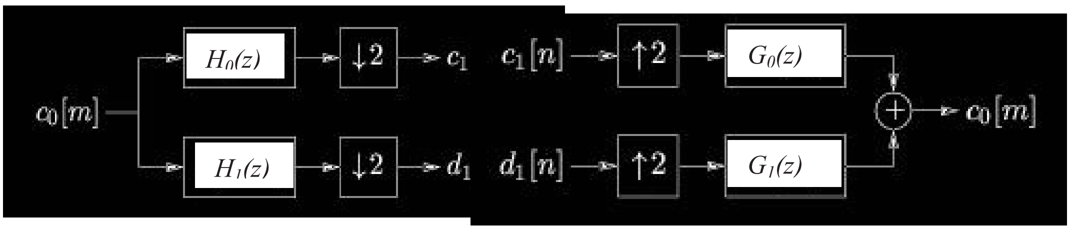

Fig. 1. Analysis filter bank, for Fast Discrete Wavelet Transform implementation. Approximation coefficients $c_1[n]$ are the Low-Pass part of $c_0[m]$, and Detail coefficients $d_1[n]$ correspond to the High-Pass part. And Synthesis Filter Bank, for Fast Discrete Inverse Wavelet Transform.

This decomposition could be iterated on the low pass component on successive stages, leading to an octave band filter bank [10], in Fig. 2, with frequencies responses of Fig. 3, if the decomposition has three levels.

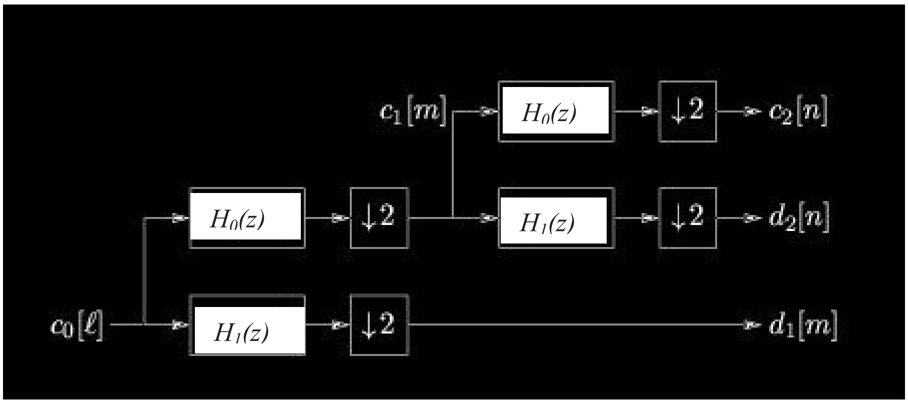

Fig. 2. A two level Analysis Filter bank implementation.

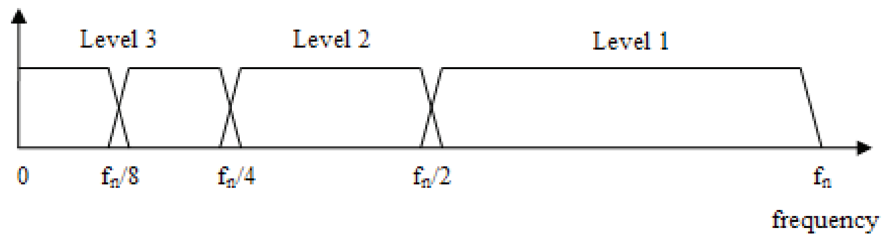

Fig. 3. Frequency response of Discrete Wavelet Analysis with 3 levels. Detail signal $d_1(m)$ is in the band from $f_n/2$ to f_n , $d_2(m)$ in the band from $f_n/4$ to $f_n/2$, $d_3(m)$ is from $f_n/8$ to $f_n/4$, and approximate signal $c_3(m)$ is from 0 to $f_n/8$

In order to achieve perfect reconstruction the relation of Z-Transform of the filters like 9/7 Cohen-Daubechies-Feauveau biorthogonal wavelet [6], must accomplish,

$$\begin{aligned} H_1(z)\cdot G_1(z)+H_0(z)\cdot G_0(z)=2 \\ G_0(z)\cdot H_0(-z)+G_1(z)\cdot H_1(-z)=0 \end{aligned} \quad \textbf{(1)}$$

3 Quantization of wavelet coefficients at all the stages, midtread vs. midrise.

Most of the compression methods based on transforms achieve their compression rate using fewer bits than the original ones with the codification of transformed coefficients [4]. Depending on the number of bits assigned we define the number of quantification steps. In the case of 3 bits for quantification, the quantification could be done with a midtread quantizer Fig. 4 (a), using 7 levels, or with a midrise quantizer Fig. 4 (b), using 8 levels.

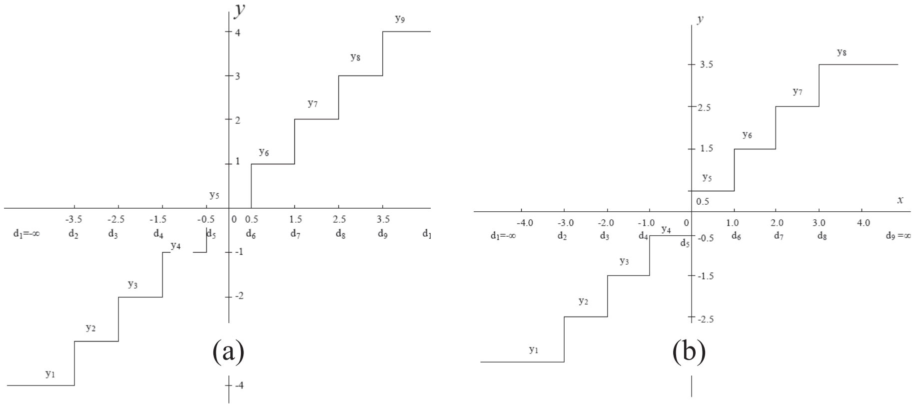

Fig. 4. 3 bits midtread uniform quantizer (a) with 7 levels and 3 bits midrise uniform quantizer (b) with 8 levels of quantification.

4 Proposed method

We propose a data compressor following the scheme of Fig. 5, based on a Discrete Wavelet Analysis of the signal with the filter bank of the Cohen-Daubechies-Feauveau biorthogonal wavelet [6]. In this first experiment the system will have two entry parameters: the first one will be the number of stages or levels of decomposition; and the second parameter will be the numbers of bits used to quantify the components at each stage.

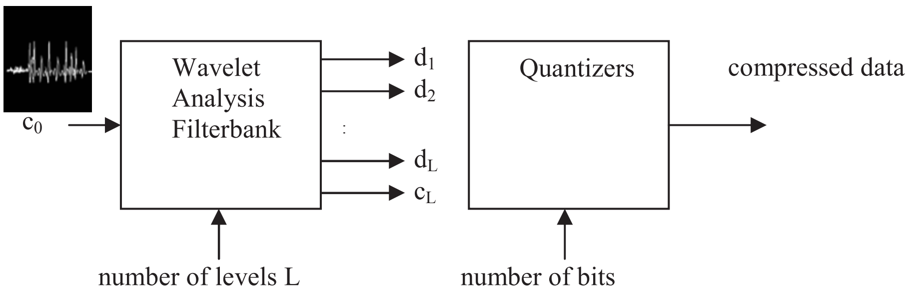

Fig. 5. Block diagram of the proposed method for the codification.

In this experiment to recover the signal we will apply a Wavelet Synthesis Filterbank on compressed data to get an approximation of the original signal. To complete the codification we should use a lossless compression on the compressed data (like run-length-coder or Lempel-Ziv [1]); this step however is out of the scope of this paper.

5 Experiments

To investigate the performance of the system we have done several experiments. We have used a voice signal (16 bits/sample, Fs=11025 Hz), a music signal (16 bits/sample and Fs=44100 Hz), and an EEG channel (16 bits/sample, Fs=250 Hz).

In the case of the voice signal (16 bits/sample, Fs=11025 Hz), the 3 stage DWA (Discrete Wavelet Analysis), leads to the signals of Fig. 6 (left). If we apply a quantification of the detail components with 3 bits, using a 7 level midtread quantifier, we get Fig. 6 (right), with a compression of 3.2:1 respect to the original data of 16 bits.

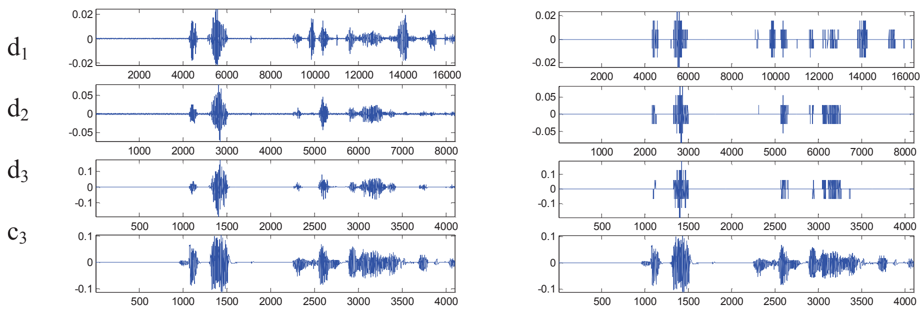

Fig. 6. Discrete Wavelet Analisis with 3 stages (left), and Quantified Discrete Wavelet Analysis with 3 bits (7 levels) (3.2:1 compression respect original signal 16 bits).

If we use this compressed data (Fig. 6) to reconstruct with the Synthesis Filter Bank, we obtain an approximation of original signal with a PSNR= 29 dB at Fig. 7. The voice is intelligible but rather noisy, compared with perfect reconstruction PSNR=100 dB, attained by the same system with 8 bits (2:1 compression).

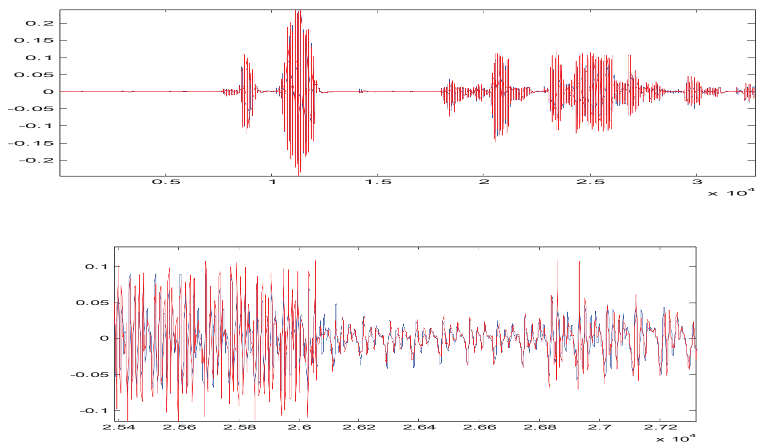

Fig. 7. Signal reconstruction (red), original voice signal (blue). Magnification of a nosy segment, PSNR=29 dB. Lossless reconstruction PSNR=100 dB.

In the case of the music signal (16 bits/sample, Fs=44100 Hz), the 3 stage DWA (Discrete Wavelet Analysis), leads to the signals of Fig. 8 (left). If we apply a quantification of the detail components with 3 bits, using a 7 level midtread quantifier, we get Fig. 8 (right), with a compression of 3.2:1 respect to the original data of 16 bits).

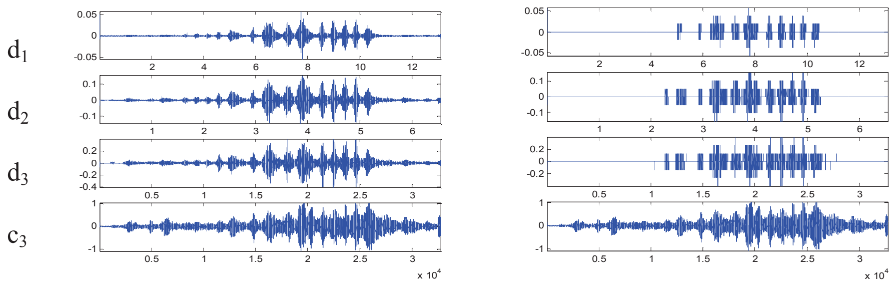

Fig. 8. Discrete Wavelet Analisis with 3 stages (left), and Quantified Discrete Wavelet Analysis with 3 bits (7 levels) (3.2:1 compression respect original signal 16 bits).

If we use this compressed data (Fig. 8) to reconstruct with the Synthesis Filter Bank, we obtain an approximation of original signal with a PSNR=32 dB at Fig. 9. The music is rather noisy, compared with perfect reconstruction PSNR= 97 dB, attained by the same system with 8 bits (2:1 compression).

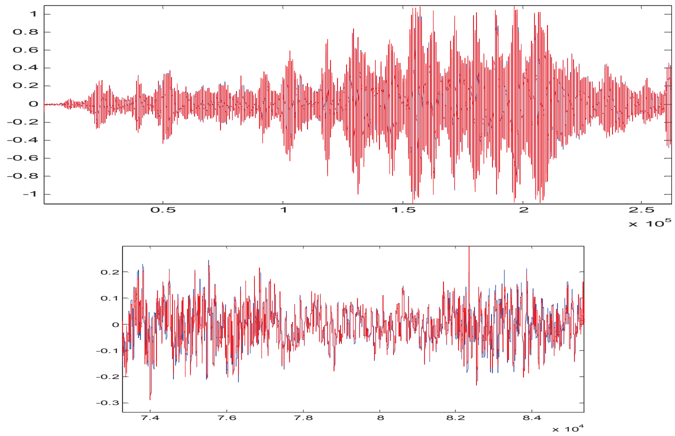

Fig. 9. Signal reconstruction (red), original voice signal (blue). PSNR=32 dB. Lossless reconstruction with music PSNR=97 dB.

In the case of the EEG signal (16 bits/sample, Fs=250 Hz), the 3 stage DWA (Discrete Wavelet Analysis), leads to the signals of Fig. 10 (left). If we apply a quantification of the detail components with 3 bits, using a 7 level midtread quantifier, we get Fig. 10 (right), with a compression of 3.2:1 respect to the original data of 16 bits.

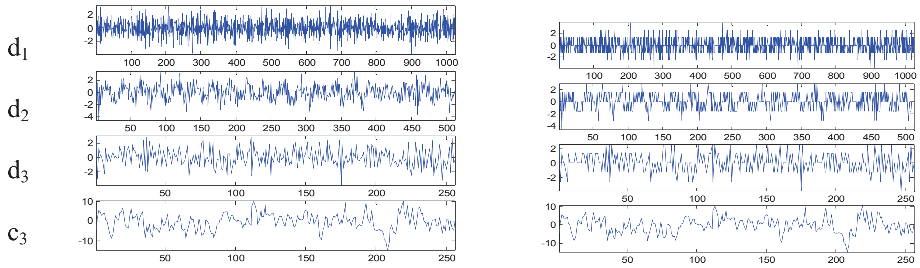

Fig. 10. Discrete Wavelet Analisis with 3 stages (left), and Quantified Discrete Wavelet Analysis with 3 bits (7 levels) (3.2:1 compression respect original signal 16 bits).

If we use this compressed data (Fig. 10) to reconstruct with the Synthesis Filter Bank, and use a midtread we obtain an approximation of original signal with a PSNR=27.48 dB at Fig. 11. The signal is quite similar to original, but with some distortion compared with perfect reconstruction PSNR= 77.6 dB, attained by the same system with 8 bits (2:1 compression).

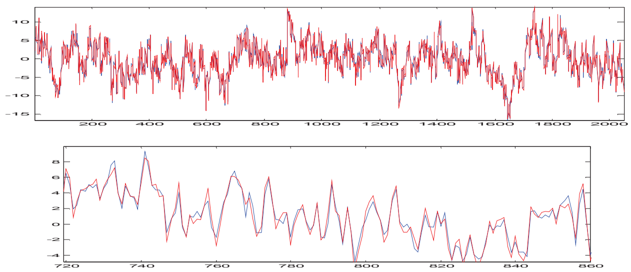

Fig. 11. Signal reconstruction (red), original EEG signal (blue). Magnification from sample 720 to 860. PSNR=27.48 dB. Lossless reconstruction with PSNR=77.6 dB.

6 Conclusions

In this paper, the use of discrete Wavelet Transform Analysis to improve a data compression codifier is explored. The preliminary results are highly positive; we reach a 2:1 of compression rate on the lossless codifiers. The compression is obtained with the quantification of detail coefficients of Discrete Wavelet Analysis with 8 bits. Quantitative measures give better PSNR with our approach than with a direct quantification of original signals with 8 bits (PSNR=50 dB), the voice signal becomes noisy; the gain on PSNR with the same rate of compression is about 50 dB.

On the other hand, with the lossy compression, we reach a scalable compression rate that ranges to from 3.2:1 to 5:1 of compression rate with PSNR results from 25 dB to 35 dB. These results are relevant and promising for the compression of natural signals, with a method that preserves transient and other relevant characteristics of the waveform, like EEG channels or ECG signals.

Future work will be done in several directions: first of all designing and exploring other families of wavelets, and other kind of signals. Another possible approach is to use frames of signals; we must then determine the length of frames related to every kind of signal. We could also try to measure the impact of different quantifiers on fidelity of reconstructed signals. It should also be interesting to study the effect of noise on coded data. Finally we need to extend these preliminary results to a wide range of measures and signals.

Annex ***PSNR***

To measure quantitatively the fidelity of a reconstructed signal we use the *PSNR* (*Peak to Signal Noise Ratio*), we have an N samples original signal c_0 , and a reconstructed signal $\hat{c}_0$ then the *PSNR*,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{c}_0(i) - c_0(i))^2}{N}}, \qquad PSNR = \frac{\max(|c_0|)}{RMSE} \tag{2}$$

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