COMPARISON OF LOSSLESS CODECS FOR SATELLITE AND MRI MEDICAL IMAGES

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ABSTRACT

In this paper, we propose derivatives of adapted nonlinear multiresolution decompositions, that allow progressive lossless image compression and that seem to be well suited to satellite images. We compare their performance (bit rate, coding time and decoding time) with different lossless codecs for MRI medical images and for satellite images. The multiresolution decompositions presented are based on a hierarchical pyramidal scheme. For one level of decomposition, the image is partitioned into two polyphase components I_1 and I_2. One component, I_2, is linearly estimated from the observation of I_1 and a causal part of I_2. The filter coefficients are computed in order to minimize either a global or a local mean square error. The difference between I_2 and its truncated linear estimation is then partitioned into two polyphase components, by decimation. Finally, the same process (decimations and estimation) is applied to I_1 in order to give two other subimages.

1 INTRODUCTION

Owing to the improvements in portable computer technology during the last decade, the digital information quantity stored and transmitted in the world has increased exponentially. Despite the constant decreasing cost of memory, it is still more and more necessary to compress data. In image compression, the progressive coding like the embedded zerotree coding introduced by Shapiro [10] has pleased many users because it gives a large flexibility. It permits users to control both the rate of data transmission and the size of memory engaged in order to store data.

In most applications of digital images, a lossy or near lossless compression is entirely satisfactory. Hence, over the last years important research works have been done on the matter, leading to the part I of the JPEG 2000 standard. However, lossless image compression finds applications in medical, seismic, satellite and military image processing. Moreover, the JPEG 2000 standard does not impose a wavelet decomposition for lossless coding. It permits innovation in the decomposition part of a lossless codec.

Hierarchical pyramidal decompositions are well suited to achieve a progressive lossy to lossless coding. The codecs JASPER [2] (compatible with the JPEG 2000 standard) and SPIHT [9] are based on such decompositions, but the LOCO-I [11] (of the JPEG-LS standard) and the CALIC [12] codecs are not. On the one hand, the S + P transform and the integer to integer wavelet transform, which are the multiresolution decompositions used in SPIHT and JASPER respectively, do not adapt to the encoded image. But on the other hand, the LOCO-I and CALIC codec do adapt to the context of the encoded image. Moreover, progressive coding is not allowed with LOCO and CALIC, yet it occurs with SPIHT and JASPER.

In [3] and [4], we have presented nonlinear adapted multiresolution decompositions based on least square estimations. They do not assume special spectral density models, as in the adaptive lifting scheme presented in [5]. Associated with the set partitioning in hierarchical trees (SPIHT) coder [9], they permit embedded progressive coding both in quality (signal to noise ratio) and in resolution ([3]) or just in resolution ([4]).

In this paper, we present derivatives of these decompositions that suit better to MRI medical images and to satellite images. This is done in section 2. In section 3, we compare the performances in bit rate, coding time and decoding time between the codecs we introduced and other ones which are well known: CALIC, LOCO-I, JASPER and SPIHT.

2 ADAPTED MULTIRESOLUTION DECOMPOSITIONS

In this section, we describe two derivatives of nonlinear multiresolution decomposition which adapt to the initial image and which are based on truncated linear mean square estimation (LMSE) associated with a lifting scheme [6]. Let us recall, in short, the methods introduced in [3] and [4]. In order to achieve one level of decomposition, the initial image I is partitioned into two subimages I_1 and I_2 by decimation. The subimages I_1 and I_2 are the polyphase components of I. The decimation is either in quincunx (QD) or separable (SD), in this case the lines are first decimated. Let us introduce the set $\mathbb{Z}$ of integer numbers and the dimension $M_2 \times N_2$ of the subimage I_2. The pixel $I_2(i,j)$ is estimated by

$$\hat{I}_2(i,j) = \sum_{(h,k)\in\Delta_1} a_{hk} I_1(i-h, j-k) + \sum_{(h,k)\in\Delta_2} b_{hk} I_2(i-h, j-k) \qquad (1)$$

where the finite subset $\Delta_1 \subset \mathbb{Z}^2$ is either a rectangle centered in $(0,0)$ (global case below mentioned) or a subset of such a rectangle (adaptive case below mentioned), and $\Delta_2 \subset \mathbb{Z}^2$ is either a finite non symmetric half plane (global case) or a subset of it (adaptive case).

The filters coefficients a_{hk} and b_{hk} are calculated in order to adapt the best (in L^2) to the initial image I. The adaptation is either global ([3]), i.e. minimizes the total energy

$$W = \sum_{i=1}^{M_2} \sum_{j=1}^{N_2} \left(I_2(i,j) - \hat{I}_2(i,j) \right)^2, \qquad (2)$$

or adaptive ([4]), i.e. minimizes the current energy

$$W = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(I_2(i,j) - \hat{I}_2(i,j) \right)^2 \alpha^{m-i+n-j}, \qquad (3)$$

with $\alpha = 0.9995$ a forgetting factor. Thereafter, the subimage I_2 is first replaced by the error of estimation

$$\tilde{I}_2(i,j) = I_2(i,j) - \texttt{floor}[\hat{I}_2(i,j) + 1/2] \qquad (4)$$

and then decimated, either in quincunx (when QD) or separately on columns (when SD) in order to give two subimages I_{21} and I_{22}.

Let us notice that in the methods described here no estimation is applied in the decomposition of I_2 into I_{21} and I_{22}, as opposed to the methods presented in [3] and [4]. Indeed, we noticed that an estimation in this step of the decomposition does not improve the compression bit rate in general, but on the contrary increases it. However, an estimation in this step slightly reduces the energy of the transformed image.

The same scheme (decimation + truncated linear estimation) is applied to the subimage I_1, giving the subimages I_{11} and I_{12}. The transformation

$$I \mapsto \begin{bmatrix} I_{11} & I_{21} \\ I_{12} & I_{22} \end{bmatrix} \qquad (5)$$

corresponds to one level of decomposition. The subimages I_{12}, I_{21} and I_{22} are the subimages of details and I_{11} is the low resolution subimage. As in the hierarchical pyramidal scheme, the multiresolution decomposition is obtained by applying recursively the one level decomposition to the low resolution subimage. In the following, the global and adaptive methods will be respectively named BBG and BBA.

2.1 Global method (BBG)

In this case, the filters coefficients a_{hk} and b_{hk} are solutions of the well known system of linear equation associated with LMSE. The matrix $\mathbf{\Gamma}$ of the system is computed from the relation

$$\mathbf{\Gamma} = \mathcal{X}^t \mathcal{X}, \qquad (6)$$

where $\mathcal{X}$ is a matrix which is made up of blocks, each block being Toeplitz, and whose coefficients are pixel values of the image I. We have implemented a kind of fore-windowed method and we have used the fact that the matrix $\mathbf{\Gamma}$ can be shared into four blocks, each block being closed to Toeplitz by blocks (the displacement rank [8] is equal to 2). This permits us to reduce significantly the complexity of matrix $\mathbf{\Gamma}$ computation and therefore to reduce significantly the coding time.

In order to better fit the orders (p,q) of the transfert function of the filters (a_{hk}) and (b_{hk}), we made a lot of tests on seventeen MRI medical images of dimension $512 \times 512 \times 8$. The best results of our simulations have been achieved by adapting the orders (p,q) to the dimension of the low resolution subimage. We noticed that the more the level of decomposition increases, the less the pixels of the low resolution subimage are correlated (as we could expect), and hence we noticed that it becomes less efficient to adapt the filters coefficients. For low resolution subimages of small dimension, the estimation $\hat{I}_2(i,j)$ in the relation (1) is replaced by a nonlinear approximation of $I_1(i,j)$ close to the transformed image of the first encoder in the LAR method introduced by Déforges et Ronsin [7].

2.2 Adaptive method (BBA)

In this case, the filters coefficients a_{hk} and b_{hk} depend on the current pixel (i,j). They are grouped in one column matrix $\underline{c}(i,j)$ and they are arranged in such an order that in the estimation equation (1), which can be written as

$$\hat{I}_2(i,j) = \underline{c}^t(i,j)\underline{y}(i,j), \qquad (7)$$

the first coefficients of the observation vector $\underline{y}(i,j)$ contain the values of the closest pixels to the current one [4]. Among these pixels, a quantity r_1 belongs to the subimage I_1 (in a neighborhood of $I_1(i,j)$) and a quantity r_2 belongs to the subimage I_2 in the non symmetric half plane neighborhood of $I_2(i,j)$.

Adaptive prediction is attractive in a coding context mainly for two reasons. First, signal-dependent filter coefficients need not be transmitted as side information and do not take up a fraction of the available bit rate. Our choice of adaptive filters in the subband coding context is motivated by the fact that images are non stationary signals: they are often made up of relatively large textured regions separated by sharp edges. An adaptive system is able to track non stationary signal.

Im.	LOCO	CALIC	BBA	JASPER	SPIHT	BBG
1	2.27	2.20	2.38	2.58	2.41	2.41
2	2.54	2.34	2.16	1.69	2.59	2.24
3	2.24	2.17	2.43	2.62	2.47	2.47
4	2.57	2.37	2.10	1.69	2.59	2.22
5	2.02	1.96	2.08	2.24	2.09	2.09
6	2.36	2.17	1.89	1.54	2.36	2.15
7	1.72	1.64	1.57	1.51	1.95	1.81
8	3.12	2.93	2.69	2.19	3.12	2.63
9	3.23	3.12	3.28	3.51	3.28	3.28
10	3.39	3.17	2.63	2.31	3.31	2.77
11	2.69	2.50	2.05	1.80	2.69	2.29
12	2.63	2.44	2.24	1.83	2.64	2.23
13	2.59	2.40	2.05	1.74	2.57	2.17
14	2.87	2.64	2.22	1.90	2.80	2.30
15	3.40	3.25	3.87	4.01	3.82	3.82
16	5.27	5.09	5.16	5.22	5.04	5.03
Av.	2.81	2.65	2.55	2.40	2.86	2.62

Table 1: Bit rate in bit per pixel (bpp), for 16 images of dimension $512 \times 512 \times 8$. The last row shows the means.

time	LOCO	CALIC	BBA	JASPER	SPIHT	BBG
cod.	0.12	0.21	3.27	0.40	0.36	3.19
dec.	0.11	0.26	3.20	0.37	0.35	0.46

Table 2: CPU time average, in seconds, for coding (first row) and decoding (last row) the MRI images of Table 1.

time	LOCO	CALIC	BBA	JASPER	SPIHT	BBG
cod.	0.19	0.31	3.46	0.51	0.42	3.52
dec.	0.15	0.32	3.41	0.47	0.40	0.68
cod.	0.31	0.95	13.96	2.17	1.74	16.46
dec.	0.39	1.33	13.59	1.98	1.66	2.88
cod.	0.14	0.23	2.43	0.30	0.32	3.19
dec.	0.14	0.25	2.38	0.28	0.29	0.42

Table 3: CPU time average, in seconds, for coding (cod.) and decoding (dec.) the satellite images of Table 4 (first and second rows for images of dimension $512 \times 512 \times 8$, third and fourth rows for images of dimension $1024 \times 1024 \times 8$ and fifth and sixth rows for images of dimension $802 \times 212 \times 8$).

3 COMPARISON OF LOSSLESS CODECS

The global method described in the previous section allows progressive coding both in quality (i.e. in signal to noise ratio) and in resolution. Indeed, the filters coefficients (truncated with a finite precision) are transmitted in the header of the bit stream. On the other hand, the above mentioned adaptive method allows only progressive coding in resolution. Indeed, the filters coefficients are not transmitted in this case, and when the decoder tries to construct a rough image from the truncated bit stream (arranged in an order that permits progressive coding in quality), it cannot retrieve the filters coefficients values (even roughly) from a partial information of the error signal $\tilde{I}_2$. Then the decoding algorithm quickly diverges.

Let us recall that on the one hand, the algorithms JASPER and SPIHT allow progressive coding in both quality and resolution, but on the other hand, the algorithms LOCO-I and CALIC allow no progressive coding. For each image, the result shown in the SPIHT column of tables 1 and 4 gives the best one obtained between the two options (smooth image or not) of the algorithm.

In this section, we show and compare the results we have obtained for two classes of images directly affected by lossless compression: that is MRI medical images and satellite images. The results have been obtained on a PC with a Pentium III 700 and 256 Mo RAM. All the programs have been compiled with Visual C++.

3.1 MRI medical images

In Table 1, we present the compression bit rate for 16 medical MRI images of dimension $512 \times 512 \times 8$. When we compare the three codecs that permit progressive coding both in resolution and quality (i.e. JASPER, SPIHT and BBG), we note that each time that BBG appreciably improves the compression bit rate, with respect to SPIHT (i.e. for images 2, 4, 6–8, 10–14), JASPER reduces much more the compression bit rate. Inversely, each time that BBG improves appreciably the compression bit rate with respect to JASPER, SPIHT gives roughly the same result as BBG, moreover, SPIHT coding is appreciably quicker than BBG coding (see the table 2). We note that BBA method gives in general a smaller compression bit rate than BBG, nevertheless it has the same behaviour as BBG when it is compared with SPIHT and JASPER. Moreover, the BBA method gives decoding times appreciably greater than all the others. Finally, we note that on average progressive coding with BBA, JASPER and BBG, gives smaller bit rate than LOCO and CALIC. In order to explain why JASPER gives appreciably smaller bit rate on average, let us recall that MRI images are obtained after a low-pass filtering and that their spectra vanish outside a disk centered in 0. Hence, it is clear that zero trees (due to that fact) will appear more often in the multiresolution decomposition of JASPER, based on a wavelet transform, than in the other multiresolution decompositions based on prediction.

3.2 Satellite images

In Table 4, we compare the compression bit rate of the above mentioned methods for satellite images. These images have been given as a favor by the French National Center of Spatial Studies (CNES) and by the so-

Im.	LOCO	CALIC	BBA	JASPER	SPIHT	BBG
1	3.81	3.72	3.85	4.01	3.89	3.88
2	5.25	5.12	5.14	5.36	5.15	5.10
3	4.13	3.65	4.24	4.43	4.27	4.25
4	4.26	4.03	4.01	4.24	3.85	3.76
5	4.98	4.87	4.95	5.11	4.93	4.95
6	4.83	4.71	4.77	4.92	4.76	4.77
7	4.41	4.28	4.28	4.44	4.31	4.26
8	5.34	5.22	5.30	5.44	5.26	5.30
9	5.21	5.09	5.15	5.30	5.12	5.17
10	4.54	4.44	4.48	4.61	4.47	4.49
11	4.18	4.07	4.03	4.42	4.32	4.26
12	4.98	4.84	4.79	5.31	5.22	5.14
13	5.13	4.92	4.96	5.50	5.41	5.34
Av.	4.70	4.53	4.61	4.85	4.69	4.67

Table 4: Bit rate (in bit per pixel) for satellite images of Genova (1), Toulouse (2), Washington (3), planet Mars (4), Oakland (5–7), San Francisco (8–10) and Moissac (11–13). The dimensions of images 1–4, 5–10 and 11–13 are respectively $512 \times 512 \times 8$, $1024 \times 1024 \times 8$ and $802 \times 212 \times 8$. The last row shows the averages.

ciety named SPOT Image. We note that JASPER gives almost always (except for the fourth image—a seeing of the planet Mars) the greatest bit rate, due to the fact that the spectra of satellite images occupies all the frequencies. Moreover, we note that CALIC method gives almost always the smallest bit rate—except for the fourth image—, this is due to the local stationarity of satellite images (hence it is worth while adapting to the context). Nevertheless, it is not worth while using multiresolution decomposition like in BBA method, because the subimages of details have a few redundancy of zeros between different levels of decomposition. Moreover, the average time decoding of BBA method is appreciably greater than the others (see Table 3). However, we note that for the view of the ground of the planet Mars, the method BBG gives appreciably smaller bit rate than the others. For this image, the method BBA can also give a smaller bit rate (3.85 bbp with the parameter values $r_1 = 11$ and $r_2 = 5$) but with an appreciably increase of coding and decoding times. The methods we introduced can be appreciably improved, by adjusting parameters like orders or thresholds to a class of images, as for example the class of satellite images of virgin areas, i.e. natural areas that have not been modified by human beings. Moreover, the same decoder can be used for all the families of images.

4 CONCLUSION

In this paper, we have shown derivatives of adapted multiresolution decompositions that allow progressive lossless image coding and that seem to be well suited to satellite images. We compare the compression bit rate, time coding and time decoding of different lossless image codecs. The performance of the codec can be increased by specializing the coder to a special class of images.

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