SATELLITE IMAGE COMPRESSION BY DIRECTIONAL DECORRELATION OF WAVELET COEFFICIENTS

X. Delaunay [1], *M. Chabert* [2], *V. Charvillat* [2], *G. Morin* [2], *and R. Ruiloba* [3]

[1] TéSA/CNES/NOVELTIS, Toulouse, France
[2] IRIT/ENSEEIHT, Toulouse, France
[3] NOVELTIS, Ramonville-Saint-Agne, France
xavier.delaunay@tesa.prd.fr

ABSTRACT

This paper presents a satellite image compression scheme based on a post-processing of the wavelet transform of images. The bandelet transform is a directional post-processing of wavelet coefficients. Thanks to a low computational complexity, this transform is a good candidate for future on-board satellite image compression systems. First, we analyze the ability of the bandelets to exploit directional correlations between wavelet coefficients. This study leads to an improved post-processing with a better decorrelation of adjacent wavelet coefficients in the vertical or in the horizontal direction taking into account the wavelet subband orientations. To perform even better decorrelation, bases are also build by Principal Component Analysis (PCA). This results in an improved compression performance without increasing the computational complexity.

Index Terms— Image coding, wavelet transforms, decorrelation, discrete transforms, satellite applications

1. INTRODUCTION

The discrete wavelet transform associated with subband coding provides high image compression ratio. Although the wavelet transform performs well on smooth areas, the wavelet representation of edges is not sparse. Indeed, wavelet coefficients have high magnitude around the edges and correlations between those coefficients remain. Therefore, great efforts have been made in the design of coding schemes to handle the redundancy near the edges. Morphological coding schemes [1, 2] are examples of coders designed to exploit clusters of high magnitude wavelet coefficients. The significance propagation pass in EBCOT coder [3], which is part of the JPEG2000 standard, has the same goal. The CCSDS (Consultative Committee for Space Data Systems) recommendation for image data compression [4] specially targets on-board spacecraft compression. In this recommendation, wavelet coefficient redundancy is exploited in a tree-like coding scheme.

Some transforms derived from the wavelets provide sparser representations of edges. Some of them are not suited for image compression since they use redundant representations [5, 6]. On the contrary, the orthogonal bandelet transform [7] is critically sampled which makes it attractive for image compression. It is an adaptive linear post-processing of an orthogonal wavelet transform. The wavelet subbands are split into blocks and transformed using an orthogonal basis selected in a dictionary. A practical bandelet scheme for image compression has been proposed in [8]. It is called the bandelet transform by grouping. It is easier to implement than [7] and thus a better candidate for on-board compression. It uses a dictionary of directional bases built by grouping wavelet coefficients along the same direction and transforming them in discrete polynomial bases.

In this paper, the goal is to prove that it is possible to enhance the compression performance by further decorrelation of the wavelet coefficients. We first analyze the directional bases built in [8] for the grouping bandelet transform and then, we propose new bases which are better suited to decorrelate the wavelet coefficients in the different subbands. In section 2, we briefly review how the directional bandelet bases have been built as well as the practical bandelet compression scheme. In section 3, we analyze the ability of the bandelet bases to capture directional correlations. Based on the observation of this section, we propose extended grouping configurations in section 4 and we build new dictionaries of orthogonal bases which better decorrelate wavelet coefficients. Even better decorrelation is obtained with bases learned by Principal Component Analysis (PCA). Finally, in section 5, we compare compression results obtained with the new dictionaries on a test set of Earth observation images to the results obtained using an implementation of the bandelet transform, the CCSDS coder [4], and JPEG2000 [3] and show that better decorrelation leads to better compression results.

2. BANDELET TRANSFORM

This section presents an overview of the grouping bandelet transform which has been proposed in [8] for image compression. The reader is referred to [7, 8] for a complete overview of the bandelet theory. In the following, the size of blocks is set to 4×4. This size has been determined based on empirical compression results and on intra-band statistical analysis of wavelet coefficients. Indeed, the wavelet coefficient dependency is very low for a distance larger than 4 pixels.

2.1. Grouping bandelet bases dictionary

The grouping bandelet dictionary proposed in [8] is composed of $N_{\mathcal{B}} = 12$ directional bases. They have been built by linking coefficients along the same direction as displayed on figure 1. Nevertheless, some coefficients cannot be linked in the appropriate direction. Those coefficients are thus linked either in the vertical or in the horizontal direction.

Discrete orthonormal Legendre polynomial bases are assigned to each of these groupings. Those bases have been plotted on figure 2. Polynomials up to a degree $n-1$ are used for the groupings of n coefficients. This finally results in a dictionary $\mathcal{D} = \{\mathcal{B}_b\}_{b=1}^{N_{\mathcal{B}}}$ of $N_{\mathcal{B}} = 12$ bases of $\mathbb{R}^M$ denoted by $\mathcal{B}_b = \{\phi_{b,m}\}_{m=1}^{M}$. As the block size is 4×4, $M = 16$. The M vectors $\phi_{b,m}$ of two of these bases are displayed on figure 3.

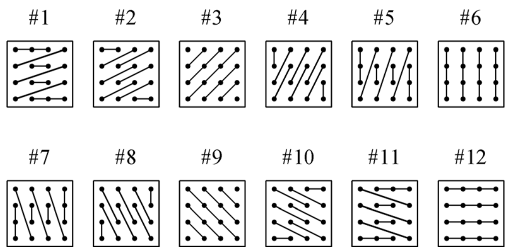

Fig. 1. Grouping configurations in $N_{\mathcal{B}} = 12$ directions. A direction corresponds to a basis.

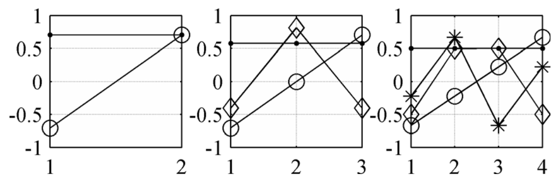

Fig. 2. Discrete orthonormal Legendre bases in dimension 2 to 4.

2.2. Bandelet analysis

The bandelet analysis process is the following:

Wavelet transform of the image
foreach *subband* **do**
  Split the $subband$ into blocks 4×4
  foreach *block* f **do**
    foreach *basis* $\mathcal{B}_b$ *of the dictionary* $\mathcal{D}$ **do**
      Transform the block of wavelet coefficients f in the basis $\mathcal{B}_b$:

$$f_b = \sum_{m=1}^{M} < f, \phi_{b,m} > \phi_{b,m}$$

      Quantize the coefficients f_b: $f_{b\triangle} = Q_\triangle(f_b)$
    end
    Keep the representation $f^*_{b\triangle}$ which minimizes the rate-distortion criterion:

$$\mathcal{L}(f_{b\triangle}) = D(f_{b\triangle}) + \lambda R(f_{b\triangle}) \qquad (1)$$

$$f^*_{b\triangle} = \underset{\{f_{b\triangle}\}_{b=0}^{N_{\mathcal{B}}}}{\arg\min}\ \mathcal{L}(f_{b\triangle})$$

  end
end

In the previous formula, $Q_\triangle$ represents a dead zone uniform quantizer and Δ the quantization step. The best representation $f^*_{b\triangle}$ of one block may be its representation into quantized wavelet coefficients denoted by $f_{0\triangle}$ with $b = 0$. In this case, no bandelet transform is applied to this block.

2.3. Rate-distortion criterion

The distortion $D(f_{b\triangle})$ in the rate-distortion criterion (1) is the square error between the coefficients f_b and the quantized coefficients $f_{b\triangle}$:

$$D(f_{b\triangle}) = \|f_b - f_{b\triangle}\|^2$$

The estimated bit-rate $R(f_{b\triangle})$ is decomposed into two parts:

$$R(f_{b\triangle}) = R_C(f_{b\triangle}) + R_b$$

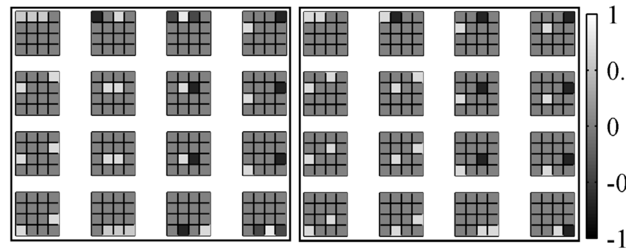

Fig. 3. Basis vectors for directional bases #1 and #2 of $\mathbb{R}^{16}$.

The first part $R_C(f_{b\triangle})$ is the bit-rate needed to encode the quantized coefficients $f_{b\triangle}$ and is estimated by:

$$R_C(f_{b\triangle}) = \sum_{m=0}^{M-1} \log_2 \frac{1}{p(f_{b\triangle})}$$

The probabilities $p(f_{b\triangle})$ are estimated by the histogram of wavelet coefficients in each subband.
The second part R_b is the bit-rate needed for the signaling of the best basis according to the rate-distortion criterion (1) and is estimated by:

$$R_b = -\log_2 p_b \quad \text{with} \quad p_b = \begin{cases} 0.5 & \text{if } b = 0 \\ 0.5/N_{\mathcal{B}} & \text{if } b \in \{1, \dots, N_{\mathcal{B}}\} \end{cases}$$

This gives greater importance to the wavelet representation of the coefficients of a block ($b = 0$). As in [7], the Lagrangian parameter λ in the rate-distortion criterion (1) is set to:

$$\lambda = \frac{3\Delta^2}{4\gamma_0} \quad \text{with } \gamma_0 = 7.$$

The quantized bandelet coefficients are encoded using an adaptive arithmetic coder. The signaling of the best basis for each block is also coded using an arithmetic coder and is part of the final bitstream. In section 5, the same compression scheme is used but with new dictionaries of bases. Note that on-board spacecraft, embedded coder with lower complexity are preferred. For example Rice-Golomb codes are used in the bit plane encoder of the CCSDS [4].

3. ANALYSIS OF INTRA-BLOCKS WAVELET CROSS-CORRELATIONS

This section analyzes first the intra-block cross-correlations between each pair of wavelet coefficients in 4×4 blocks and second the ability of the directional bases to capture these correlations. A bandelet analysis has been performed on a training set of 7 large (1024×1024) 12-bit satellite images. This analysis is done off-line and different images were used for the tests of compression performance in section 5. The quantization step as been set to $\Delta = 40$. With this quantization step, the resulting bit-rate is about 2 bpp which is the targeted bit-rate for on-board compression.

For the analysis of intra-band wavelet correlations, the subbands HL_1, LH_1 and HH_1 of the wavelet transforms of the whole training set of images are processed separately. $N_{\mathcal{B}}$ sets of blocks of wavelet coefficients are build. The set #*b* contains the blocks of wavelet coefficients f for which the rate-distortion criterion (1) is minimized by the quantized representation $f_{b\triangle}$. In other words, the set #*b* contains the blocks of wavelet coefficients which should be transformed in the directional basis $\mathcal{B}_b$ for the compression. This basis corresponds to the grouping configuration #*b* in figure 1. Once these $N_{\mathcal{B}}$ sets have

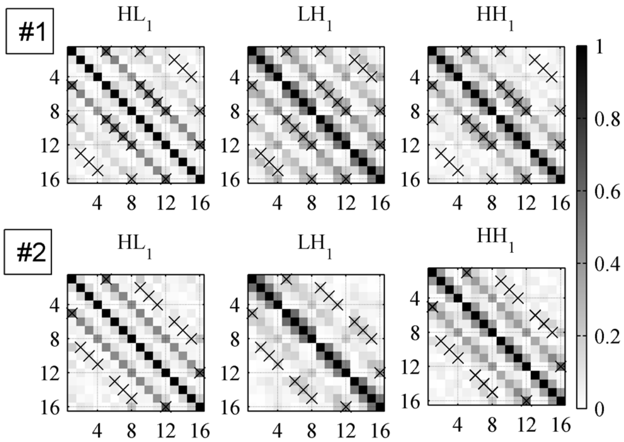

Fig. 4. Correlation matrices between the 16 wavelet coefficients of a block for the sets #1 and #2 in the three subbands HL_1, LH_1, and HH_1. The wavelet coefficients are numbered column-wise in the blocks.

been built, the correlation matrix is computed for the blocks f in the same set. This shows the intra-block cross-correlations between wavelet coefficients. Correlation matrices of the sets #1 and #2 in the subbands HL_1, LH_1, and HH_1 are displayed in absolute values on figure 4. The wavelet coefficients are numbered column-wise in the blocks.

On figure 4, strong correlations can be observed between horizontally adjacent wavelet coefficients in the subband HL_1 and between vertically adjacent wavelet coefficients in the subband LH_1. These negative correlations are due to the high-pass filtering in the wavelet decomposition. On the correlation matrices of figure 4, the coefficients associated to the groupings shown on figure 1 are marked with a cross. For example, in configuration #1, the coefficients 2 and 13 are linked together, so there is a cross on the correlation matrices at the coordinates (2,13) and (13,2). Strong correlations were expected at these coordinates due to the groupings and the rate-distortion minimization. Nevertheless, it can be seen that the cross-correlation between linked wavelet coefficients are small, except for the coefficients linked with their neighbors in the vertical or horizontal directions. The same observation can be done for all the grouping configurations of figure 1.

In conclusion, the directional bandelet bases fail in catching directional correlations. This can be explained by the low correlations between non-adjacent wavelet coefficients and in other directions than horizontal or vertical. Furthermore, consider a subband of an image and the best directional bases for each block of that subband. It can be observed that only a few of them correspond to an underlying edge in the good direction. Yet, compression results with these directional bases are good. Consequently, these directional groupings are kept in the new grouping configurations proposed in the next section.

4. NEW DICTIONARIES OF BASES

It has been shown in section 3 that the strongest correlations are between wavelet coefficients which are adjacent in the horizontal direction in the HL subbands and between wavelet coefficients which are adjacent in the vertical direction in the LH subbands. Correlations between coefficients linked in other directions are low. Thus, to enhance the compression performance, two different approaches are proposed.

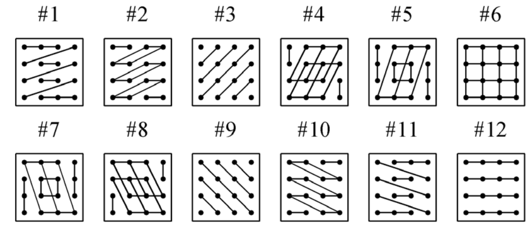

Fig. 5. Extended grouping configurations in $N_{\mathcal{B}} = 12$ directions for the subbands HL.

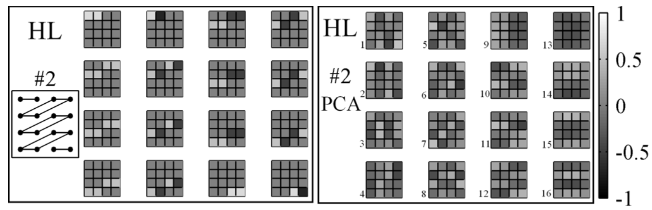

Fig. 6. Bases #2 for the HL subbands extracted from the new dictionary of groupings and the dictionary built by PCA.

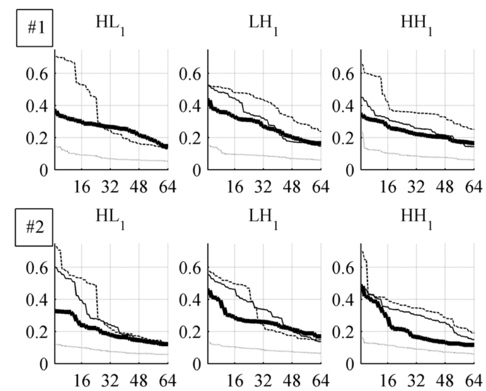

Fig. 7. Comparisons of intra-band cross-correlations between the wavelet coefficients (dashed line), the bandelet coefficients (solid line), the coefficients in the new bases of groupings (bold line), and in the bases build by PCA on the training image set (thin line). Correlation coefficients have been computed on a test image set and sorted in decreasing order. Only the first 64 correlation coefficients are plotted for the blocks in the set #1 and #2. Cross-correlations in the new bases are lower than the ones in the bandelet bases.

4.1. Extended groupings

The groupings of the bandelet transform are extended in the vertical and horizontal directions. As the correlations are different in the subbands, the new grouping configurations differ for the subbands HL, LH and HH. Parallel groupings of same size are horizontally linked in the HL subbands, they are vertically linked in the LH subbands and linked in either directions in the HH subbands. The new grouping configurations for the HL subbands are plotted in figure 5. As groupings are now bi-dimensional, 2D bases of Legendre polynomials have been built by tensor products of 1D Legendre polynomials. This finally results in one dictionary of $N_{\mathcal{B}} = 12$ bases for each HL, LH and HH subband. The basis #2 extracted from the dictionary for the subband HL is displayed on figure 6.

Figure 7 shows that the cross-correlations between coefficients in the new bases of groupings are lower than the ones in the bandelet bases. Since the grouping configuration #1 has not been changed in the subband HL_1 (figure 5), the results are the same for the bandelets and the new coefficients in this case.

4.2. Bases learned by PCA

Cross-correlations can also be eliminated by PCA on each of the $N_{\mathcal{B}}$ sets of blocks per subband built in section 3. Those PCA generate $N_{\mathcal{B}}$ bases which define one dictionary of linear transforms per subband learned on the training set of images. On figure 6, the basis built by PCA on the set of blocks #2 extracted from the subbands HL is displayed. Figure 7 shows that on the test image set, the correlations between coefficients in bases learned by PCA are very low.

The dictionaries of bases are then used to compress the test image set to obtain the results shown in section 5. We shall see that both approaches to build new bases give better compression results than the bandelets.

5. COMPRESSION RESULTS

In this section, the results obtained with the new dictionaries are compared to the results obtained with the bandelet transform, the CCSDS coder for on-board spacecraft compression and JPEG2000. The compression results reported on figure 8 are averaged results obtained on six Earth observation images from PLEIADES satellite and PELICAN airborne sensor. PLEIADES first satellite is to be launched in 2009 and images used are simulated images. PLEIADES and PELICAN images have a spatial resolution of respectively 70 cm and 20 cm, their size is 1024×1024 and their bit-depth is 12-bits. The target PSNR for on-board compression is 50 dB.

For the evaluation of the performance, the same lossy wavelet transform as in [4] is used: 9/7 CDF (Cohen-Daubechies-Feauveau) filters and three levels of decomposition. Differences between the results obtained with the two proposed transforms, the bandelet transform and the wavelet transform, all followed by the same adaptive arithmetic coder, are plotted on figure 8. The gain over the wavelet transform is more than 0.8 dB at a bit-rate of 2 bpp. Although, the computational complexity of the proposed transforms are the same as the computational complexity of the bandelet transform, at a bit-rate of 2 bpp, the quality of the decompressed images is increased by more than 0.1 dB with the bases built with the extended groupings and by more than 0.2 dB with the bases learned by PCA.

It can also be seen on figure 8, that JPEG2000 performance is about 0.5 dB higher than the results obtained with the bases learned by PCA. The performance of the CCSDS coder is 0.5 dB lower than the results obtained with the extended groupings. The difference in performance between the CCSDS coder and JPEG2000 is due to the choice of low complexity in the CCSDS recommendation. Indeed for on-board compression, real-time processing is required with space qualified electronics. Thus, for on-board compression, the design of a low complexity embedded coder adapted to the post-transforms should be inspired from the CCSDS coder.

6. CONCLUSION & PERSPECTIVE

This study has shown that it is possible to enhance the compression performance by decorrelation of wavelet coefficients. In this approach, the bandelet transform can be outperformed by exploiting correlations between vertically or horizontally adjacent wavelet coefficients in accordance to the direction of the high-pass wavelet filter. We have also shown that there exist only weak correlations in other directions than the vertical or the horizontal. To further enhance the decorrelation, we have built bases by performing a PCA on the different sets of blocks built by bandelet analysis. Even though there is scarcely visible directional information in these bases, the improvement in decorrelation of the coefficients results in a improvement of compression performance. Thus, the directional properties of the bases are not essential to improve the compression. At the scale of 4×4 blocks, compression is mainly improved in the two directions of the wavelet filters. At last, to achieve even better compression performance, an adapted EBCOT coder can be applied after the proposed transforms. However, on-board compression requires a low computational complexity and thus the design of a coder inspired from the CCSDS recommendation should be preferred.

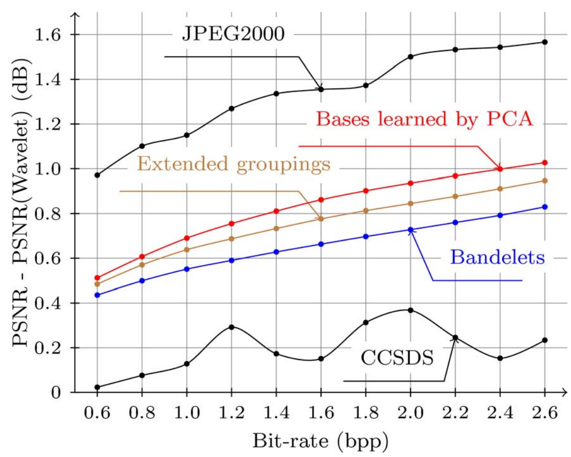

Fig. 8. Comparison of compression performance using the extended groupings and the bases learned by PCA to the bandelet transform. The results are plotted relative to the compression performance of the wavelet transform coupled to the same arithmetic coder as the other transforms. JPEG2000, and the CCSDS use different coders.

7. ACKNOWLEDGMENTS

This work has been carried out under the financial support of the French space agency CNES (www.cnes.fr) and NOVELTIS company (www.noveltis.fr). We would like to thank G. Peyré for the software components provided.

8. REFERENCES

[1] S.D. Servetto, K. Ramchandran, and M.T. Orchard, "Image coding based on a morphological representation of wavelet data," *IEEE Trans. on Image Process.*, vol. 8, no. 9, pp. 1161–1174, Sept. 1999.

[2] B-B Chai, J. Vass, and X. Zhuang, "Significance-linked connected component analysis for wavelet image coding," *IEEE Trans. on Image Process.*, vol. 8, no. 6, pp. 774–784, June 1999.

[3] D.S. Taubman and M.W. Marcellin, *JPEG2000: Image compression fundamentals, standards and practice*, Kluwer Academic Publishers, 2001.

[4] CCSDS, *Image Data Compression Recommended Standard CCSDS 122.0-B-1 Blue Book*, Nov. 2005.

[5] E.J. Candes and D.L. Donoho, *Curvelets - a surprisingly effective nonadaptive representation for objects with edges*, Vanderbilt University Press, Nashville, TN, 1999.

[6] M.N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation," *IEEE Trans. on Image Process.*, vol. 14, no. 12, pp. 2091–2106, Dec. 2005.

[7] G. Peyré and S. Mallat, "Discrete bandelets with geometric orthogonal filters," in *IEEE Int. Conf. on Image Process.*, Sept. 2005, vol. 1, pp. I– 65–8.

[8] G. Peyré, *Géométrie multi-échelles pour les images et les textures*, Ph.D. thesis, Ecole Polytechnique, 2005.