ADAPTIVE LIFTING FOR MULTICOMPONENT IMAGE CODING THROUGH QUADTREE PARTITIONING

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ABSTRACT

The objective of this paper is the design of adaptive quincunx lifting schemes for lossless compression of multiband images. More precisely, the operators of the lifting scheme are modified according to the local activity of the multivariate input signal. To this respect, a block-based adaptive strategy is adopted: the image is partitioned into a quadree structure and a couple of optimal operators is assigned to each resulting volumetric segmented block. Our main contribution consists of a suitable quadtree partitioning rule that takes into account simultaneously the spatial and spectral redundancies. Simulations performed on real satellite images show that the proposed adaptive method outperforms the conventional non-adaptive lifting schemes.

1. INTRODUCTION

The development of multimedia applications combined with the improvement of the radiometric, spectral and, spatial resolutions of imaging systems generates huge amounts of digital data to be stored and transmitted. For example, in remote sensing applications, a Thematic-Mapper Landsat image requires several hundreds of megabytes and about 5,000 images are generated weekly. The need for data compression is obvious but some applications such as remote sensing require lossless compression to ensure an accurate exploitation of the data (e.g. computation of physical ground parameters). Besides, resolution scalability is a desired functionality for image telebrowsing, its key issue consisting in generating a multiresolution representation of the input image. The up-to-date lossless coders make use of second generation of wavelet transforms derived from Lifting Schemes (LS) [1]. Moreover, in the case of multispectral images, an efficient representation of both spatial and spectral redundancies is possible thanks to Vector Lifting Schemes (VLS) [2]. Generally, the operators involved in such decompositions are the same for all the pixels of the input image. However, a significant improvement is achieved when the local statistics of the input image are taken into account. Different adaptive strategies were reported. The first one consists in using adaptive operators whose weights are modified iteratively from the input data [3] or from the local gradient information [4, 5, 6]. In [7], instead of using the same predictor and update for the whole blocks, we have obtained improvements by switching between predetermined couples of operators according to the local statistics of the considered blocks. However, it is worth pointing out that the method we proposed so far, employs blocks that have the same size. Recently, we have introduced more flexibility by employing variable size blocks but this approach was restricted to the case of monocomponent image [8]. In this paper aims at extending such variable size block-based procedure to the compression of *multicomponent* images.

The paper is organized as follows. In Section 2, a brief overview of nonseparable quincunx vector lifting scheme is given. In Section 3, we describe the generalized adaptive lossless coder. Simulation results are given and some conclusions are established in Section 4.

2. VECTOR QUINCUNX LIFTING SCHEMES

Generally, the LS is applied in a separable manner for 2D signals but nonseparable quincunx lifting schemes (QLS) were found very appealing [9, 10] mainly, for two reasons. Firstly, they are suitable for the coding of images digitized on a quincunx sampling grid. Secondly, the involved operators may be more appropriate to describe the spatial content of natural images. The description of a generic QLS requires to define some notations. Let us denote by $\{x^{(b)}(m,n)\}_{\{b=1,\dots,B\}}$ the input image formed by B spectral channels. The quincunx sampling (with a sampling step equal to 1) generates the sampled image $a^{(b)}_{1/2}(m,n) = x^{(b)}(m-n, m+n)$. More generally, $a^{(b)}_{j/2}(m,n)$ denotes the approximation of the b-th band at resolution $j/2$, $j \in \mathbb{N}^*$, when a multiresolution analysis of the quincunx sampled image is performed. A generic QLS consists of three main operations. These are applied globally to the whole spectral bands. The first one starts by splitting $a^{(b)}_{j/2}(m,n)$ into two polyphase components $x^{(b)}_{j/2}(m,n)$ and $\tilde{x}^{(b)}_{j/2}(m,n)$:

$$\begin{cases} x^{(b)}_{j/2}(m,n) &= a^{(b)}_{j/2}(m-n, m+n) \\ \tilde{x}^{(b)}_{j/2}(m,n) &= a^{(b)}_{j/2}(m-n+1, m+n) \end{cases} . \quad (1)$$

The second step is a decorrelation step: the $\tilde{x}^{(b)}_{j/2}(m,n)$ samples are predicted by the samples of the current band. Then, the residual prediction coefficients $d^{(b)}_{(j+1)/2}(m,n)$ are computed:

$$d^{(b)}_{(j+1)/2}(m,n) = \tilde{x}^{(b)}_{j/2}(m,n) - \lfloor \mathbf{x}^{(b)}_{j/2}(m,n)^T \mathbf{p}^{(b)}_{j/2} \rceil, \quad (2)$$

where $\mathbf{x}^{(b)}_{j/2}(m,n)$ is the reference data prediction vector containing some $a^{(b)}_{j/2}(m,n)$ samples and, $\mathbf{p}^{(b)}_{j/2}$ is the vector of prediction weights. Finally, the approximation $a^{(b)}_{(j+1)/2}(m,n)$ of $x^{(b)}(m,n)$ at lower resolution results from the update of the $x^{(b)}_{j/2}(m,n)$ samples by the residual prediction coefficients $d^{(b)}_{(j+1)/2}(m,n)$. So, we calculate

$$a^{(b)}_{(j+1)/2}(m,n) = x^{(b)}_{j/2}(m,n) + \lfloor \mathbf{d}^{(b)}_{j/2}(m,n)^T \mathbf{u}^{(b)}_{j/2} \rceil, \quad (3)$$

where $\mathbf{d}^{(b)}_{j/2}(m,n)$ is the reference detail vector and, $\mathbf{u}^{(b)}_{j/2}$ is the vectors of update weights.

To better cope with the multiband nature of multispectral images, we have defined the quincunx *vector* lifting scheme (QVLS) [10]. More precisely, the $d^{(b)}_{(j+1)/2}$ and $a^{(b)}_{(j+1)/2}$ coefficients are computed by using the coefficients of the b-th band *and* the *other* spectral bands. A basic example of QVLS consists in considering the following neighboring samples of pixel $(m-n+1, m+n)$:

$$\mathbf{x}^{(b_1)}_{j/2}(m,n) = \begin{pmatrix} a^{(b_1)}_{j/2}(m-n, m+n) \\ a^{(b_1)}_{j/2}(m-n+1, m+n-1) \\ a^{(b_1)}_{j/2}(m-n+1, m+n+1) \\ a^{(b_1)}_{j/2}(m-n+2, m+n) \end{pmatrix}, \quad (4)$$

$$\text{and } \forall i > 1, \quad \mathbf{x}^{(b_i)}(m,n) = \begin{pmatrix} a^{(b_i)}_{j/2}(m-n, m+n) \\ a^{(b_i)}_{j/2}(m-n+1, m+n-1) \\ a^{(b_i)}_{j/2}(m-n+1, m+n+1) \\ a^{(b_i)}_{j/2}(m-n+2, m+n) \\ a^{(b_{i-1})}_{j/2}(m-n+1, m+n) \\ \vdots \\ a^{(b_1)}_{j/2}(m-n+1, m+n) \end{pmatrix}, \quad (5)$$

where $(b_1, \dots, b_B)$ denotes a permutation of $(1, \dots, B)$. It is worth mentioning that the component b_1 acts as a reference component for the intercomponent prediction of the other components b_i ($i \neq 1$). For the sake of simplicity, no update is performed:

$$\forall j = 1, \dots, J \quad \forall i = 1, \dots, B, \quad \mathbf{u}^{(b_i)}_{j/2} = \mathbf{0}. \quad (6)$$

3. PROPOSED ADAPTIVE METHOD

3.1. Motivation

The performance of the previous QVLS depends on the choice of vectors $\mathbf{p}^{(b)}_{j/2}$. Instead of using a fixed vector, improvement is expected by accounting for the local statistics of the input subbands. More precisely, we consider a block-based adaptation procedure coupled to a classified prediction approach. To this respect, the original multicomponent image is viewed as a volume of data (according to the spatial and spectral dimensions). The objective is to segment the image into nonoverlapping volumetric blocks of variable size, each segment or class being assigned to an optimal predictor. Obviously, the key issues are both the optimization of the underlying predictors and, the volumetric block-segmentation procedure.

3.2. Prediction optimization

Within each class c, the B predictors are computed by minimizing the overall rate. However, the bit-rate criterion is strongly dependent on the retained entropy coder. This is the reason why we prefer to consider the global entropy $\mathcal{H}^{(c)}_J$ of a J-stage decomposition, as a performance criterion. It is defined as the average of the entropies $\{\mathcal{H}^{(b,c)}_J\}_{b=1}^B$ of the representations of the B bands:

$$\mathcal{H}^{(c)}_J \triangleq \frac{1}{B} \sum_{b=1}^{B} \mathcal{H}^{(b,c)}_J. \quad (7)$$

In turn, $\mathcal{H}^{(b,c)}_J$ is the weighted sum of the entropies of the approximation and, the detail subimages:

$$\mathcal{H}^{(b,c)}_J \triangleq \left[\sum_{j=1}^{J} (0.5)^j \mathcal{H}^{(b,c)}_{d,j/2} \right] + (0.5)^J \mathcal{H}^{(b,c)}_{a,J/2} \quad (8)$$

where $\mathcal{H}^{(b,c)}_{d,j/2}$ (resp. $\mathcal{H}^{(b)}_{a,J/2}$) denotes the entropy of the detail (resp. approximation) coefficients of the b-th channel within the given class c.

3.3. Adaptation through quadtree decomposition

Concerning the block-partitioning, we propose to apply a *quadtree* decomposition (QT) since the quadtree is a hierarchical data structure that enables a simplified description of the regions within a given image. Its construction requires the definition of a predetermined segmentation rule $\mathcal{R}$ tailored to the compression application. A splitting approach or a merging approach can be envisaged to build a quadtree structure. The first technique operates in a top-down manner. The image is partitioned in 4 volumetric quadrants. Each quadrant can be subdivided into 4 smaller volumetric subblocks if the rule $\mathcal{R}$ is satisfied. Then, the subdivision procedure is repeated recursively until either there is no further splitting needed or the minimum block size $k_1 \times k_2$ is reached. The resulting segmented structure is described by the quadtree. Each node of the quadtree is uniquely associated with a volumetric subblock. The size and the location in the image of the volumetric subblock can be easily derived from the position in the tree of the corresponding node. In contrast, the alternative method (the merging procedure) is a bottom-up construction method. Indeed, we start by partitioning the image into subblocks of minimum size $k_1 \times k_2$. Then, each four adjacent volumetric subblocks (called children) are tested to know whether they are homogeneous w.r.t. the rule $\mathcal{R}$. If the test is positive, the 4 children subblocks are merged into a father subblock which has 4 times the size of its children. Again, the merging procedure is recursively applied until the largest block size (generally, the image) is reached.

3.4. The proposed algorithm

Our contribution consists in *coupling* the construction of the quadtree with the adaptation of the lifting operator. For example, let us consider the top-down quadtree partitioning.

• **INIT** The father block f is the whole multispectral image, its four children $c_1, \ldots, c_4$ correspond to the first 4 quadrants.

• **OPTIM** For each spectral component b, the predictors $\mathbf{p}_{j/2}^{(b,f)}$ and $\mathbf{p}_{j/2}^{(b,c_i)}$ of a J-stage QLS that are optimal in the sense of the detail variance or the entropy, are computed for $i = 1, \ldots, 4$ and, $J = 1, \ldots, J$. Let $\mathcal{H}_J^{(b,f)}$ and, $\mathcal{H}_J^{(b,c_i)}$ denote the entropy of the considered blocks.

• **TEST SPLITTING** We have to check whether the splitting of the father f into its 4 children yields a more compact representation than the single father block does. In other words, we have to check whether the following criterion $\mathcal{R}$ is satisfied:

$$\frac{1}{4B}\sum_{i=1}^{4}\left(\sum_{b=1}^{B}\mathcal{H}_J^{(b,c_i)}\right)+o(c_i) < \frac{1}{B}\left(\sum_{b=1}^{B}\mathcal{H}_J^{(b,f)}\right)+o(f), \tag{9}$$

where $o(n)$ denotes the coding cost of the side information required by the decoding procedure at node n. Indeed, if the average coding cost of the 4 children is smaller than the father coding cost, then the splitting of the current father-quadrant into 4 chidren quadrant is retained. Then, the previous procedure is applied successively and separately to the resulting four children. Otherwise, the splitting of the father-node is not advantageous and the father quadrant is viewed as a leaf-node. The procedure is repeated until block size $k_1 \times k_2$ is reached. In a similar manner, it is easy to derive the bottom-up construction of the quadtree.

3.5. Evaluation of the coding cost

The side information contains information about the tree decomposition and the predictors used in the QVLS. A coding procedure is indeed required to describe the tree structure. Generally, the bit "1" is assigned to a parent node and the bit "0" to a leaf so that a binary sequence is associated with each leaf node. Obviously, the image pixels may always be considered as leaves. Therefore the tree structure coding can be stopped one level before the deepest level. Then, a run-length coding can be applied to the resulting set of binary sequences. Finally, the prediction coefficients $\mathbf{p}_{j/2}^{(b_i)}$ must also be transmitted. As they can take floating values, they cannot be encoded in a lossless manner. Therefore, they have to be rounded prior to the arithmetic coding stage. The detail coefficients $d_{(j+1)/2}^{(b_i)}(m,n)$ have then to be computed again with the new values of the rounded prediction coefficients. Finally, it is worth mentioning that we have chosen to code the side information by variable-length and arithmetic coders because the latter are known to achieve a rate very close to the entropy of the underlying source symbols.

4. EXPERIMENTAL RESULTS

First of all, we would like to illustrate visually the QT decomposition procedure on a monocomponent image. In Figure 1, the top-down QT decomposition procedure is illustrated for the monocomponent "Barbara" image of size 512 × 512. The resulting decomposition provides 19 leaves with different sizes. It should be noted that the macroblocks correspond to the spatially homogeneous regions. Concerning the multispectral images, we have used SPOT images with respectively $B = 3$ ("Tunis87") and $B = 4$ components ("Kairouan"). We have also used a set of $B = 7$ spectral bands corresponding to a Thematic Mapper scene called "Trento". All the tested images are of size 512 × 512, each component being coded at 8 bpp. Table 1 provides the average entropy with intra-band mode (QLS) and inter-band mode (QVLS) of the quadtree-adaptation procedure. We note that the inter-band coding gives an important contribution to reduce the coding cost of multispectral images compared to the intra-band coding whatever the band-ordering is. However, some band-ordering yields more compact representations than others and they are related to the mutual redundancies between the spectral components. For example, concerning "Trento" image, the difference between the intra and inter coding amounts 1.2618 bpp in the case of the band-ordering (6,7,1,2,3,4,5). This represents a substantial gain in the context of lossless coding. Finally, a comparison with the *separable* 5/3 transform which was adopted in the lossless mode of the JPEG2000 standard (with an equivalent number of decomposition stages) indicates that the inter mode, adaptive quadtree-based technique can be viewed as a competitive lossless coding method.

5. REFERENCES

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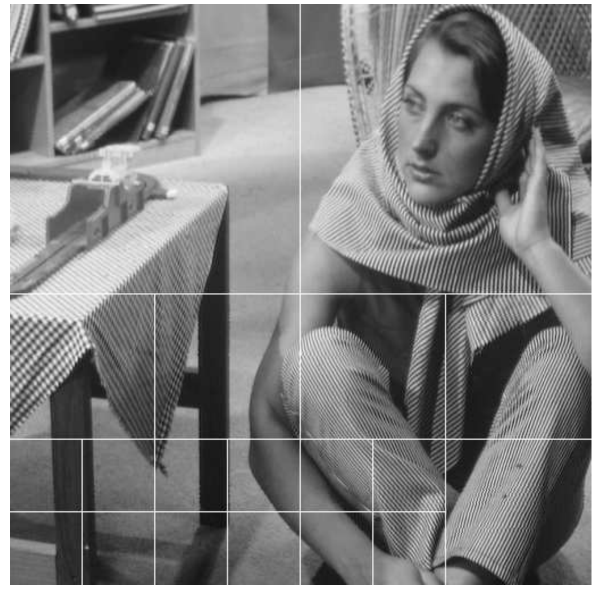

Fig. 1. Top-down approach, the resulting quadtree decomposition of the monocomponent image has 19 leaves: 2 blocks (256×256), 5 blocks (128×128) and 12 blocks (64×64).

Table 1. Average entropy (in bpp), a four-stage decomposition is used in the non separable case and a two-stage separable decomposition is performed concerning the 5/3 transform.

Image	Band-ordering	5/3	QT, intra (QLS)	QT, inter (QVLS)
Trento	1,2,3,4,5,6,7	3.5247	3.8101	3.7450
	2,3,4,5,6,7,1		3.0627	**2.8957**
	3,4,5,6,7,1,2		3.4052	3.3866
	4,5,6,7,1,2,3		5.1190	4.8977
	5,6,7,1,2,3,4		5.1448	4.9711
	6,7,1,2,3,4,5		3.8851	2.6233
	7,1,2,3,4,5,6		4.0683	3.8936
Tunis87	1,2,3	2.9004	2.7411	2.8697
	2,3,1		2.9900	2.9487
	3,1,2		3.0159	**2.7465**
Kairouan	1,2,3,4	4.7544	4.4933	4.2042
	2,3,4,1		4.3893	**4.0290**
	3,4,1,2		3.8787	4.2339
	4,1,2,3		3.9760	4.1520