A BLOCK-BASED PREDICTIVE LOSSLESS CODER FOR QUINCUNX MULTISPECTRAL IMAGES

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ABSTRACT

In this paper, we are interested in designing lossless coders for a class of multispectral images. More precisely, we consider quincunx sampled images such as those encountered in new generation satellite imaging systems. Our approach exploits both the spatial and the spectral correlations existing in these images by applying block-adaptive predictors. A clustering algorithm is applied to the spectral bands of the original image in order to compute optimal predictors within each group of blocks. Simulation tests carried out on natural multicomponent images show that the proposed adaptive interband differential prediction outperforms state-of-art lossless coders.

1 INTRODUCTION

Multispectral images are widely used in several applications such as remote sensing, pre-press color images, SAR imaging, ... These images are supplied by several sensors operating in different spectral channels. Therefore, several spectral components are generated for a single sensed area. With the continuous improvement of imaging systems, increasing amounts of images are produced. Thus, the storage of huge volumes of data is required and data compression becomes a key component of storage systems. A great number of coding methods were developed for still images [1]. Generally speaking, image coding algorithms are divided into two categories: lossy and lossless. With lossless coders, the compressed data flow must allow the original data to be exactly recovered. Because of the constraint of perfect reconstruction, lossless coders yield much less compact representations than the lossy ones. However, lossless coders are mandatory for several applications. In particular, for remote sensing, the exact reproductibility of the images is often required since physical ground parameters can be computed from the decoded images. According to some experts, this parameter estimation could be affected by lossy coding algorithms.

In this paper, our objective is to design efficient predictive coders for multispectral images. More specifically, we will be interested in quincunx sampled multispectral images. Indeed, some of the most recent sensors for satellite imaging systems provide quincunx sampled images. For example, the upcoming SPOT 5 satellite uses this kind of sampling. In this context, it is important to design appropriate reversible predictive coders taking into account the particular characteristics of quincunx sampling. Note that some recent works have considered quincunx lifting structures so as to design efficient lossy coders for monoband images [2]. In our work, the multicomponent nature of the images we consider is taken into account by applying hybrid (spatial and spectral) predictive coders. Furthermore, a block-adaptive strategy is adopted in order to switch between the predictors according to the local spatial and spectral image contents. The remainder of this paper is organized as follows. In Section 2, we give a short overview of differential predictive methods dedicated to multispectral images. In Section 3, we present a new hybrid lossless coder. Some experimental results are presented and some conclusions are drawn in Section 4.

2 A BRIEF OVERVIEW

Usually, spatial and spectral correlations are exploited by conventional coders initially developed for natural monoband images. Among the various methods, differential predictive coding is probably the most simple and efficient exact coding technique and it has been used for about fourty years. Following a specific scanning order, the intensity of the current pixel is predicted from the intensities of the neighboring pixels. Then, the prediction error is coded. There are various coders based on DPCM techniques [3]. For instance, an Optimal Linear Predictor (OLP) based on the previous neighbors can be applied. The optimal coefficients in the sense of the prediction Mean Squared Error (MSE), are solutions of the well-known Yule-Walker equations. To circumvent the resolution of these normal equations, it is possible to use predetermined coefficients for the predictors as in the lossless mode of the JPEG standard [4]. Similarly, the Consultative Committee for Space Data Systems has adopted a standard for lossless data compression, characterized by a prediction stage followed by Rice entropy encoding [5]. Initially, the applied predictor was a 1D nearest-neighbor predictor (a basic purely spatial predictor). An effort has been made in order to propose other predictors (spatial, spectral or hybrid) [6]. Very often, the proposed predictors are concerned with rectangularly sampled images. In the sequel, we propose to design predictors suitable for *multispectral* images resulting from a *quincunx* sampling.

3 PROPOSED APPROACH

More precisely, let $x^{(b)}(m,n)$ denote the b-th spectral component of a multispectral image ($b = 1,\dots,B$) and let $(b_1,\dots,b_B)$ denote a specific permutation of the B bands. For simplicity sake, $x^{(b)}(m,n)$ is assumed to correspond to a rectangularly sampled image but, due to quincunx subsampling, only the pixels such that $(m+n) \bmod 2 = 0$ are available and can thus be processed.

Firstly, the pixels $x^{(b_1)}(m,n)$ such that $(m+n) \bmod 2 = 0$ are predicted using their causal neighbors:

$$\mathbf{x}_r^{(b_1)}(m,n) = \begin{pmatrix} x^{(b_1)}(m,n-2) \\ x^{(b_1)}(m-1,n-1) \\ x^{(b_1)}(m-2,n) \\ x^{(b_1)}(m-1,n+1) \end{pmatrix}. \quad (1)$$

Then, the interband correlation existing between the remaining spectral bands b_i $(2 \le i \le B)$ is exploited by hybrid predictions based on the following pixels:

$$\mathbf{x}_r^{(b_i)}(m,n) = \begin{pmatrix} x^{(b_i)}(m,n-2) \\ x^{(b_i)}(m-1,n-1) \\ x^{(b_i)}(m-2,n) \\ x^{(b_i)}(m-1,n+1) \\ x^{(b_{i-1})}(m,n) \\ \vdots \\ x^{(b_1)}(m,n) \end{pmatrix}. \quad (2)$$

Denoting by $\lfloor \cdot \rceil$the truncation to the nearest integer, the pixel intensities are exactly recovered from the prediction errors $x^{(b_i)}(m,n) - \lfloor (\mathbf{a}^{(b_i)})^T \mathbf{x}^{(b_i)}(m,n) \rceil$ $(i = 1,\dots,B)$, if the decoding process starts with b_1 followed by b_2 and so on.

Instead of coding the whole spectral band with the same predictor, better compression is achieved by taking into account the nonstationarity of the input images. Two basic alternatives have already been proposed: adaptive DPCM and classified DPCM [7]. In the first one, the coefficients are iteratively updated from the input data. In the second one, R classes are firstly determined and then, each class is associated with an optimized predictor, applied to all the pixels of this class. It is also possible to combine adaptive and classified prediction [8]. In this paper, we use switched predictors. More precisely, each spectral band $x^{(b)}(m,n)$ is partitioned into non-overlapping blocks of size $t_h \times t_l$. These blocks are classified into C_b regions $\mathcal{R}_1^{(b)},\dots,\mathcal{R}_{C_b}^{(b)}$. The prediction coefficients $\mathbf{a}_1^{(b)},\dots,\mathbf{a}_{C_b}^{(b)}$ applied in each region should reflect the local features of the region. The chosen predictors are identified with a binary map of size $\lceil \log_2(\prod_{b=1}^{B} C_b) \rceil$. Obviously, for each B-block, the index of this binary vector should be sent to the decoder leading to an overhead not exceeding:

$$o = \frac{\lceil \sum_{b=1}^{B} \log_2 C_b \rceil}{B t_h t_l} \text{ (bpp)}. \quad (3)$$

Note that the amount of side information can be further reduced by differential encoding. It is worth pointing out that the classification rule is the main issue in this approach. In the context of exact coding, such classification/adaptation procedure should minimize the overall rate [9]. However, the direct minimization of such a function is computationally extensive and involves entropy coders to be calculated reliably. Suboptimal strategies such as the use of neural networks [10] could be adopted but they are sensitive to local minima.

Here, we propose to minimize iteratively the MSE rather than the bitrate according to a clustering algorithm which is a generalization of the classical Lloyd-Max algorithm used for vector quantizer design [11]. It is a block-based training algorithm similar to the classified adaptive predictor described in [12]. The clustering algorithm proceeds as follows.

1. The prediction coefficients are initially set to some default values.

2. For the given set of predictors, the blocks of band b are classified into one of the C_b decision regions so as to minimize the Mean Square prediction Error (MSE). This assignment is analogous to the nearest neighbor rule in vector quantization.

3. For each given class, the minimum MSE linear predictor is computed through the resolution of the normal equations.

4. Steps 2 and 3 are repeated until the MSE converges to a (possibly local) minimum.

This algorithm is applied sequentially to the B spectral bands but, as in the case of fixed prediction, some caution should be taken concerning the band ordering. This block-based training algorithm generates appropriate prediction weights adapted to the nonstationary contents of the multispectral image.

4 EXPERIMENTAL RESULTS

The test images are 512×512 SPOT images with a radiometric precision of 8 bpp. The first image "Tunis" corresponds to a 3-band ($B = 3$) image depicting the urban area of the city of Tunis (Tunisia). It is a complex city scene that contains high frequency details such as building structures and roads. The second image "Kairouan" is 4-band image ($B = 4$) concerning a rural region near the city of Kairouan (Tunisia). Obviously, the performance of the proposed coder depends strongly on the choice of the reference band b_1. We select the band which is the most correlated to the remaining bands and in both cases, the spectral component XS2 was found to be the most appropriate ($b_1 = 2$, $b_2 = 1$, $b_i = i$ for $i > 2$). The coder performance is measured by the average entropy $\mathcal{H} = o + \frac{\sum_{b=1}^{B} \mathcal{H}^{(b)}}{B}$ where $\mathcal{H}^{(b)}$ is the zero-th entropy associated with the b-th band. We have used the same number of classes: $C_b = 3$ for $b = 1, \ldots, B$. The clustering algorithm was applied to 8×4 blocks. The involved overhead amounts to 0.052 bpp for "Tunis" and to 0.055 bpp for "Kairouan" which is a very small fraction of the overall value of $\mathcal{H}$. From Tables 1 and 2, it can be noted the good performances of adaptive prediction compared with non-adaptive techniques even for a small number of predictors. Block-based adaptive algorithm can achieve dramatic entropy decreases, up to 1.7179 bpp for "Tunis", for purely spatial DPCM. Furthermore, by taking into account simultaneously the spatial and the spectral redundancies, higher compression ratios are obtained. Finally, Figures 1 and 2 illustrate the decay of the entropy and the MSE with respect to the iteration number of the clustering algorithm.

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Table 1: "Tunis" image: entropies (in bpp) obtained with different predictors.

Predictor	$\mathcal{H}^{(b_1)}$	$\mathcal{H}^{(b_2)}$	$\mathcal{H}^{(b_3)}$	$\mathcal{H}$
Spatial Fixed	5.3880	5.2090	4.8336	5.1435
Spatial Adaptive	3.6969	3.5974	3.3602	3.5619
Hybrid Fixed	5.3880	4.5270	4.2117	4.7089
Hybrid Adaptive	3.6969	2.9210	3.5655	**3.4256**

Table 2: "Kairouan" image: entropies (in bpp) obtained with different predictors.

Predictor	$\mathcal{H}^{(b_1)}$	$\mathcal{H}^{(b_2)}$	$\mathcal{H}^{(b_3)}$	$\mathcal{H}^{(b_4)}$	$\mathcal{H}$
Spatial Fixed	4.4366	4.4649	3.7935	3.9340	4.1572
Spatial Adaptive	4.3832	4.4062	3.7459	3.8654	4.1060
Hybrid Adaptive	4.3832	3.4633	3.7806	3.8518	**3.8843**

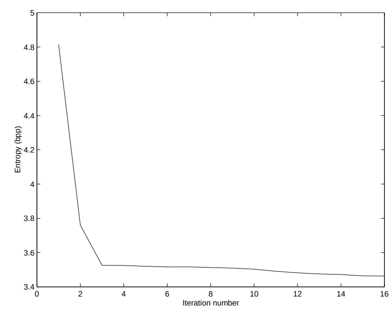

Figure 1: "Kairouan" image: variation of the entropy $\mathcal{H}^{(b_2)}$ *vs* the iteration number.

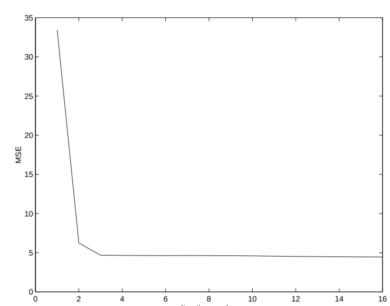

Figure 2: "Kairouan" image: variation of the MSE *vs* the iteration number.