Signal Processing 88 (2008) 2790–2803

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

# Adapted generalized lifting schemes for scalable lossless image coding

Hocine Bekkouche [a,*,1], Michel Barret [a], Jacques Oksman [b]

[a] Information, Multimodality and Signal Team, SUPELEC, 2 rue É. Belin, 57070 Metz, France
[b] Signals and Electronic Systems Team, SUPELEC, Plateau de Moulon, 91192 Gif-sur-Yvette, France

ARTICLE INFO

*Article history:*
Received 29 October 2007
Received in revised form
2 June 2008
Accepted 4 June 2008
Available online 11 June 2008

*Keywords:*
Wavelets
Adapted filter banks
Adapted lifting scheme
Adaptive filtering
Lossless image compression
Still image compression
Progressive coding
Multi-resolution analysis

ABSTRACT

Still image coding occasionally uses linear predictive coding together with multi-resolution decompositions, as may be found in several papers. Those related approaches do not take into account all the information available at the decoder in the prediction stage. In this paper, we introduce an adapted generalized lifting scheme in which the predictor is built upon two filters, leading to taking advantage of all the available information. With this structure included in a multi-resolution decomposition framework, we study two kinds of adaptation based on least-squares estimation, according to different assumptions, which are either a global or a local second order stationarity of the image. The efficiency in lossless coding of these decompositions is shown on synthetic images and their performances are compared with those of well-known codecs (S + P, JPEG-LS, JPEG2000, CALIC) on actual images. Four images' families are distinguished: natural, MRI medical, satellite and textures associated with fingerprints. On natural and medical images, the performances of our codecs do not exceed those of classical codecs. Now for satellite images and textures, they present a slightly noticeable (about 0.05–0.08 bpp) coding gain compared to the others that permit a progressive coding in resolution, but with a greater coding time.



## 1. Introduction

The lossless image compression finds applications in satellite and medical image processing, where a lossy or near lossless coding is not satisfactory. However, in many applications of lossless coding, from time to time, lossless at full resolution is not possible because the transmission channel has a limited bandpass and then coding with a smaller resolution is better than no transmission at all. In other applications, customers need lossless coding at full resolution and other ones are satisfied with smaller resolutions of the same images. Therefore, embedded progressive coding from low resolution to lossless full resolution can be a good compromise in many applications. This coding allows to reconstruct from a truncated bit flow a decompressed image, which has a smaller resolution than the encoded one. As and when the data are received, the user is capable of enhancing the image resolution, until it reaches the original quality and resolution.

It is well known that bi-orthogonal wavelet decompositions are efficient for lossy and near lossless image compression [1], this is why they are used in the ISO JPEG2000 standard. The lifting scheme, introduced by Sweldens [2] in order to construct wavelet decompositions by a simple, reversible and fast process, found quickly its main application in lossless image compression. In this case, a nonlinear filter bank with critical sampling and perfect reconstruction is obtained, with nonlinearities

* Corresponding author.
*E-mail addresses:* h_bekkouche@yahoo.com, Hocine.Bekkouche@supelec.fr (H. Bekkouche), Michel.Barret@supelec.fr (M. Barret), Jacques.Oksman@supelec.fr (J. Oksman).

[1] This work was partially supported by the Lorraine Region.

0165-1684/$ - see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.sigpro.2008.06.003

which are limited to truncations (i.e., rounding to the nearest integer) [3]. Moreover, Daubechies and Sweldens showed that any bi-orthogonal wavelet decomposition with FIR (finite impulse response) filters can be represented by a lifting scheme [4] and, therefore, all the well-known wavelets used in lossy image codecs can be quite closely approximated by integer-to-integer wavelets. The performances in lossy and lossless image compression of integer-to-integer wavelets and the S + P transform by Said and Pearlman [5] are evaluated in [6]. Hampson and Pesquet [7] proposed a structure which is more general than the lifting scheme, with an arbitrary number of channels and arbitrary nonlinear filters. It is interesting to note the simplicity of this structure and the way the perfect reconstruction is performed in an inherent manner by a synthesis filter bank "mirror" of the analysis filter bank, as in the lifting scheme. That structure, with nonlinear prediction filters based on image segmentations, has been applied for still image and video coding by Amonou and Duhamel [8].

In the standard wavelet decompositions, the filter coefficients are fixed: they do not adapt to the image as best possible. However, the lifting scheme gives an interpretation in terms of estimation (or prediction) of perfect reconstruction filter banks, associated with multi-resolution decompositions. Now, linear prediction coding (LPC) proved its great efficiency for speech coding; it found applications in mobile telephones. Therefore it is natural to study LPC in image coding. About 15 years ago, adaptive linear predictions using least-squares estimation (LSE) algorithms were tested for image compression (see [9] and its bibliography, or later [10]), but they were not associated with dyadic decompositions and consequently they were not suitable for progressive coding. More recently, Gerek and Çetin [11] used the lifting scheme with adaptive predict steps: the filter coefficients were updated to each pixel of the image, thanks to a conventional stochastic gradient algorithm, in order to minimize the variance of the detail signal. Boulgouris et al. [12], expressed each filter of the optimal $M$-subband analysis filter bank as a function of the power spectral density (PSD) of the input image. They assumed the entire image is a wide sense stationary (WSS) signal. The optimum is achieved by minimizing the mean squared error of prediction for each of the $M-1$ detail signals. Two kinds of parameterized models were assumed for the PSD of the image, i.e., the adaptation is optimum only if the PSD of the image belongs to a set of two models. The filters of the update steps did not adapt to the image, they were identical with those encountered in the lifting scheme of well-known wavelets. To improve the prediction whenever the global WSS assumption is invalid, the linear predictors were enhanced by nonlinear means, namely by directional post-processing in the quincunx decimation case, and by adaptive-length post-processing in the separable (row-column) decimation case. In [13], the authors chose locally, among a finite dictionary of wavelet filters, the filter that must be applied to the current pixel depending on its proximity with an outline: the closer the pixel is to an outline, the smaller the impulse response support of the analysis filter. In [14], the authors studied the optimization of a lifting scheme (for both the predict and update steps) associated with twofold quincunx decimation. They imposed constraints to the filters in order to avoid overflow and they applied their filter banks to lossy image compression.

In each of the above mentioned papers with adapted prediction filters, we can notice that all the information available at the decoder is not taken into account in the "predict" step.[2] Indeed, after the twofold decimation, the pixels of a subband, say $x_2$, are predicted as a linear combination of the pixels of the other subband, say $x_1$, and the pixels of subband $x_2$ are not involved in the observation vector, whereas they could be! As is done in the classical LPC. In [15], we introduced an adapted integer-to-integer multi-resolution decomposition, based on LSE and assuming global second order stationarity of the image, which takes advantage of all the information available at the decoder, and we applied it to lossless image coding. In [16], we completed this decomposition by introducing another adaptation, which assumes only local stationarity in the image. The reason that led us to carry out this study lies in the fact that the image models are not fully appropriate for entire images, they are better justified for well-chosen parts of the images taken separately. Those parts are the textured regions that can be found in most kinds of images. Then, in [17] we compared the performances of these decompositions in lossless coding of satellite and medical MRI images with well-known codecs.

In this paper, we complete the results of the conference papers [15–17] and provide more details and full proofs. First, we present the adapted generalized lifting scheme framework, which is shared both by locally and globally adapted estimation methods—we shall call them, respectively, LAE and GAE below. In Sections 3.1 and 3.2, the GAE and LAE methods are explained in details. Their efficiency in lossless coding is shown on synthetic images (Section 4) and their performances are compared with those of well-known codecs (S + P [5,18], LOCO I [19,20], CALIC [21,22], and Jasper [23]) on actual images (Section 5). We considered four families of images (natural, medical MRI, satellite and textures with fingerprints).

In the following, $\mathbb{Z}$ denotes the set of all integers. For a matrix $\mathbf{A}$, $\mathbf{A}^{\mathrm{T}}$ denotes its transpose. Underlined lower case letters denote vectors, which are identified with the column matrix of their coordinates. The symbol E denotes the mathematical expectation.

## 2. Adapted generalized lifting schemes

In this section we begin by presenting a short overview of the generalized lifting scheme in the mono-dimensional (1-D) case, then we extend it to the 2-D case, clarifying the integer-to-integer variant and the adaptation of the filters. Furthermore we explain how the generalized lifting scheme can be used in a multi-resolution framework,

[2] We should say "estimation" step, since it is not a prediction problem, but an estimation problem in estimation theory; nevertheless we chose the vocabulary used in filter bank theory.