International Journal of Electronics and Communication Engineering.
ISSN 0974-2166 Volume 7, Number 1 (2014), pp. 31-38

http://www.irphouse.com

Adaptive Lifting Schemes Combining Seminorms for Lossless and Lossy Compression

T. Manjoori and Mrs. S. Revathi Priyadharsini

PG Scholar M.E (VLSI Design) Sri Ramanujar Engineering College Chennai, India.
t.manjoori.ece@gmail.com
Department of electronics and communication engineering
Sri Ramanujar Engineering College Chennai, India
revusaran@gmail.com

Abstract

This paper presents a new class of adaptive wavelet decompositions that can capture the directional nature of the picture information. Our method exploits the properties of semi norms to build lifting structures able to choose between different update filters, the choice being triggered by a local gradient of the input. In order to discriminate between different geometrical information, the system makes use of multiple criteria, giving rise multiple choice of update filters. It establishes the conditions under which these decisions can be recovered at synthesis, without the need for transmitting overhead information.

Keywords - Wavelet transforms, image coding, Lifting structures

I. INTRODUCTION

Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. The recent growth of data intensive multimedia-based web applications have not only sustained the need for more efficient ways to encode signals and images but have made

Compression of such signals central to storage and communication technology [13].

I.1. PRINCIPLES BEHIND COMPRESSION

A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS) [13].

In general, three types of redundancy can be identified:

Spatial Redundancy or correlation between neighboring pixel values. Spectral Redundancy or correlation between different color planes or spectral bands.

Temporal Redundancy or correlation between adjacent frames in a sequence of images (in video applications). Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible.

I.2. DIFFERENT CLASSES OF COMPRESSION TECHNIQUES

Two ways of classifying compression techniques are mentioned here.

(a) Lossless vs. Lossy compression:

In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually lossless)[13].

(b) Predictive vs. Transform coding:

In predictive coding, information already sent or available is used to predict future values, and the difference is coded. Since this is done in the image or spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics [13].

Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients). This method provides greater data compression compared to predictive methods, although at the expense of greater computation [13].

I.3 WAVELETS AND IMAGE COMPRESSION:

Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function (t) as a superposition of a set of such wavelets or basis

Functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts).

Fig. 1 a: Original Lena Image.

Fig. 1 b: Reconstructed Lena to show Blocking artifacts

Since there is no need to block the input image and its basis functions have variable length, wavelet coding schemes at higher compression avoid blocking artifacts. Wavelet based coding is more robust under transmission and decoding errors, and also facilitates progressive transmission of images. In addition, they are better matched to the HVS characteristics. Because of their inherent multi resolution nature, wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important.

II. WAVELET-BASED IMAGE CODING SCHEMES

- Embedded Zero tree Wavelet (EZW) Compression.
- Set Partitioning in Hierarchical Trees (SPIHT) Algorithm.
- Scalable Image Compression with Embedded Block Coding with Optimized Truncation of the embedded bit-streams EBCOT.
- Lossless Image Compression using Integer-Integer WT.
- Image Coding using Adaptive Wavelets.

II.1 EMBEDDED ZERO TREE WAVELET (EZW) COMPRESSION

In octave-band wavelet decomposition, each coefficient in the high-pass bands of the wavelet transform has four coefficients corresponding to its spatial position in the octave band above in frequency. Because of this very structure of the decomposition, it probably needed a smarter way of encoding its coefficients to achieve better compression results.

The zero tree is based on the hypothesis that if a wavelet coefficient at a coarse scale is insignificant with respect to a given threshold T, then all wavelet coefficients of the same orientation in the same spatial location at a finer scales are likely to be insignificant with respect to T. The idea is to define a tree of zero symbols which starts at a root which is also zero and labeled as end-of-block. Many insignificant coefficients at higher frequency sub-bands (finer resolutions) can be discarded, because the tree grows as powers of four. The EZW algorithm encodes the tree structure so obtained. This results in bits that are generated in order of importance, yielding a fully embedded code.

The main advantage of this encoding is that the encoder can terminate the encoding at any point, thereby allowing a target bit rate to be met exactly. The algorithm produces excellent results ithout any pre-stored tables or

II.2 SET PARTITIONING IN HIERARCHICAL TREES (SPIHT) ALGORITHM

An alternative explanation of the principles of operation of the EZW algorithm to better understand the reasons for its excellent performance. Partial ordering by magnitude of the transformed coefficients with a set partitioning sorting algorithm, ordered bit-plane transmission of refinement bits, and exploitation of self similarity of the image wavelet transform across different scales of an image are the three key concepts in EZW. In addition, they offer a new and more effective implementation of the modified EZW algorithm based on set partitioning in hierarchical trees, and call it the spiht algorithm.

A scheme for progressive transmission of the coefficient values that incorporates the concepts of ordering the coefficients by magnitude and transmitting the most significant bits first is presented. A uniform scalar quantize made this simple quantization method more efficient than expected. Results from the SPIHT coding algorithm in most cases surpass those obtained from EZQ algorithm.

II.3. IMAGE CODING USING ADAPTIVE WAVELETS

All images are not equal, and so in wavelet-based image coding, the wavelet filter should be chosen adaptively depending on the statistical nature of image being coded. The performance in lossy coders is image dependent; while some wavelet filters perform better than others depending on the image, no specific wavelet filter performs uniformly better than others on all images. This adaptive filter selection is important because, when the performance of the wavelet filter is poor in the first place, use of even sophisticated quantization and context modeling of the transform coefficients may not always provide significant enough gain.

Hence, the importance of searching and using good wavelet filters in most coding schemes cannot be over emphasized. Wavelet based coding provides substantial improvement in picture quality at low bit rates because of overlapping basis functions and better energy compaction property of wavelet transforms. Because of the inherent multiresolution nature, wavelet-based coders facilitate progressive transmission of images thereby allowing variable bit rates.

III. PROBLEM STATEMENT

Classical linear wavelet representations of images have the drawback of not being optimally suited to represent edge information. To overcome this problem, new multiresolution decompositions have been designed that can take into account the characteristics of the input signal/image In [7], [11] we have introduced an adaptive wavelet decomposition based on an adaptive update lifting step. In particular, we have studied the case where the update filter coefficients are triggered by a binary decision obtained by thresholding the semi norm of the local gradient-type features of the input. The lifting scheme can therefore choose between two different update linear filters: if the semi norm of the gradient is above a threshold, it chooses one filter, otherwise it chooses the other.

At synthesis, the decision is obtained in the same way but using the gradient computed from the decomposition coefficients available at synthesis. With such a thresholding decision scheme, perfect reconstruction amounts to the so called

Threshold Criterion, which says that the semi norm of the gradient at synthesis should be above the threshold only if the semi norm of the original gradient is. In [7] we have derived necessary and sufficient conditions for the invariability of such adaptive schemes for various scenarios. Several simulation results have been given to illustrate the potential of our adaptive schemes for preserving the discontinuities in signals and images even at low resolutions. Furthermore, it has been shown that adaptive schemes often yield decompositions that have lower entropies than schemes with fixed update filters, a highly relevant property in the context of compression.

However, the adaptive scheme proposed in [7] is not very flexible in the sense that it can only discriminate between two ‘geometric events’ (e.g., edge region or homogeneous region). In this paper, we extend the aforementioned scheme so that it can use multiple criteria giving rise to multi-valued decision for choosing the update filters. In this way, we can discriminate between different geometric structures in order to capture the directional nature of picture information.

IV. ADAPTIVEUPDATE LIFTING

Here x(n) = x_0(2n), y(n) = x_0(2n +1) are the polyphase components of an input signal x_0. Both x and y are the input for a decision map D whose output at location n is a binary decision dn = D(x, y) (n) ^{a}{0, 1},

This decision triggers the update filter Ud and the addition d. More precisely, if dn is the binary decision at location n, then the updated value x’ (n) is given by

$$x'(n) = x(n).dnUdn(y)(n)......(1)$$

We assume that the addition d is of the form x.du =ad (x + u), where ad is a scalar normalization factor. In particular, this means that the operation d is invertible. The update filter is taken to be of the form

$$U_d(y)(n) = \sum_{i=-L_1}^{L_2} \lambda_{d,j} y_j(n)......(2)$$

Where y_j(n) = y(n+j), and L_1 and L_2 are nonnegative integers. Henceforth, we will denote j = - L_1… L_2 by j. The filter coefficients $\lambda_{d,\ j}$ depends on the decision d at location n. From (1) and (2), we deduce the update equation used at analysis

$$x'(n) = \alpha_{dn} x(n) + \sum_j \beta_{dn,j} y_j(n)......(3)$$

Where â d_j = α d λ d_j. Although it may appear at first sight that x (n) can easily be recovered by means of the formula

$$x(n) = \frac{1}{\alpha_{dn}} \left(x'(n) - \sum_j \beta_{dn,j} y_j(n) \right)......(4)$$

It is not true, in general, that perfect reconstruction holds. Toward that end, it must be possible to recover the decision dn = D(x, y) (n) from x’ (rather than x) and y.

This amounts to be problem of finding another decision n map D' such that

$$D(x, y)(n) = D'(x', y)(n)......(5)$$

If x’ is given by (1). It can be shown [8] that a necessary, but in no way sufficient, condition for perfect reconstruction is that the value kd =âd + jâd does not depend on d. Throughout the remainder of this letter, we normalize the previous constants by setting $k_0 = k_1 = 1$.

V. DECISION MAP

The decision map D is assumed to depend on the gradient vector v = (vL1, …., vL2) T given by

$$v_j(n) = x(n) - y_j(n) = x(n) - y(n + j)$$

$$j = -L_1 ... L_2 ......(6)$$

It is assumed that

$$D(x, y)(n) = [\, p(v(n)) > T\,]......(7)$$

Where [P] = 1 if the predicate P is true and 0 if false. In [8], p can be an arbitrary seminorm. Here we restrict ourselves to a so-called weighted gradient seminorm

$$p(v) = \left|a^T v\right| = \left|\sum_j a_j v_j\right| ......(8)$$

Where a ª RN is a weight vector. We are exclusively interested in the case where the decision map D' at synthesis is of the same form as, but possibly with a different threshold. To have perfect reconstruction, the condition in (5) must be satisfied, i.e.,

$$\left|a^T v(n)\right| \le T \Leftrightarrow \left|a^T v'(n)\right| \le T' ......(9)$$

where v' (n) is the gradient vector at the synthesis,
i.e., v'j (n) = x' (n) – yj (n).

Proposition 1: Under the previous assumptions, perfect reconstructions are possible if and only if one of the following two conditions holds:
1) A: =. j aj =0;
2) There exists constants γ0, γ1. R such that ¦1- γ0 A¦. ¦1- γ1 A¦, and βd, j = γd α j for d = 0, 1 and j = -L1, ….., L2.
In both cases, one can choose T'=T.

The proof of this result, as well as many others for different semi norms, can be found in [8]. Notice that the first case where A = 0 is not very interesting from a theoretical point of view, as it corresponds to

$$\left|a^T v(n)\right| = \left|a^T y(n)\right| ......(10)$$

The no adaptive case where the decision map depends only on and not on yj and not x; namely in this case.

V. RESULTS AND COMPARISONS

The Quality of the reconstructed image is measured interms of Mean square error (MSE) and Peak signal to noise ratio (PSNR). The PSNR value for different bit rates and different decomposition levels of the sharp edge preserved image and image without sharp edge as shown below.

V.1 ADAPTIVE BASED ON COMBINING NORMS

Image compression based on Adaptive Wavelet decomposition is presented. The adaptive Lifting technique includes an adaptive update lifting and fixed prediction lifting step.

Table II Peak Signal to Noise Ratio Image Circles raw (256X256)

Decom/Bit rate	1	2	3	4	5	6	7	8
0.1	5.9	9.4	13.2	16.1	15.2	13	12.8	12.2
0.5	11.8	14.2	22.2	31.9	31.7	30.6	29.9	27.5
1	14.7	22.1	43.5	49.5	50.1	49.9	50.2	48.8

V.2 NON- ADAPTIVE (HARR) LIFTING BASED IMAGE COMPRESSION

Table III Peak Signal to Noise Ratio Image Circles raw (256X256)

Decom/ Bit rate	1	2	3	4	5	6	7	8
0.1	5.9	9.5	13.2	14.5	12.7	10.4	8.5	9.3
0.5	11.8	14.1	18.17	16.53	13.7	11.5	9.6	9.32
1	14.7	20.1	19.9	16.58	13.8	11.5	9.6	9.3

The adaptive wavelet decomposition works better than non – adaptive wavelet decomposition. The Image Quality is increased by 5% for high decomposition and bit rate.

VI. CONCLUSION

Image compression based on Adaptive and Non-Adaptive Wavelet decomposition is presented. The adaptive Lifting technique includes an adaptive update lifting and fixed prediction lifting step. The adaptively here of consists that, the system can choose different update filters in two ways (i) the choice is triggered by combining the different norms (ii) Based on the arbitrary threshold. The results of adaptive and Non – adaptive based image compression are compared from the result. The adaptive wavelet decomposition works better than non – adaptive wavelet decomposition.

REFERENCES

[1] E. J. Cand`es. “The curvelet transform for image denoising” In Proceedings of the IEEE International Conference on Image Processing, Thessaloniki, Greece, October 7-10 2001.

[2] R. L. Claypoole, G. M. Davis, W. Sweldens, and R. G. Baraniuk. “Nonlinear wavelet transforms for image coding via lifting, ” IEEE Transactions on Image Processing, 12(12):1449– 1459, December 2003.

[3] A. Cohen and B. Matei. “Compact representation of images by edge adapted multiscale transforms, ” In Proceeding of the IEEE International Conference on Image Processing, Thessaloniki, Greece, October 7-10 2001.

[4] M. N. Do and M. Vetterli. “The contourlet transform, ” Submitted to IEEE Transactions on Image Processing, 2004. Transactions on Image Processing, 9(10):1649–1659, October 2000.

[5] O¨ Gerek and A. E. C¸ etin. “Adaptive polyphase sub band decomposition structures for image compression, ” IEEE

[6] H. J. A. M. Heijmans and J. Goutsias. “Nonlinear multiresolution signal decomposition schemes, ” Part II: Morphological wavelets. IEEE Transactions on Image Processing, 9(11):1897– 1913, 2000.

[7] H. J. A. M. Heijmans, B. Pesquet-Popescu and G. Piella. “Building nonredundant adaptive wavelets by update lifting, ” To appear in Applied and Computational Harmonic Analysis.

[8] S. Hsiang and J. Woods. “Embedded image coding using zeroblocks of subband/wavelet coefficients and context modeling, ” in Proceedings of the IEEE International Symposium on Circuits and Systems (Geneva, Switzerland, May 28-31, 2000), pp. 662–664.

[9] E.Le Pennec and S. G. Mallat. “Sparse geometric image representation with bandelets, ” Submitted to IEEE Transactions on Image Processing, 2004.

[10] W.Sweldens, ”The Lifting scheme:A custom-design construction of biorthogonalwavelet”J.Appl.comp.Harm.anal.vol.3.no.2pp186-200, 1996.

[11] I.Daubechies and S.Sweldens “Factoring wavelet transforms into lifting steps”tech.rep., Bell Laboratories, 1996.

[12] M.Rabbani and P.W.Jones”Digital image compression Techniques.Bellingham, W A SPIE, 1991

[13] Sachin Dhawan”A review of image compression and comparison of its algorithms”IJECT vol 2, issue 1, march2011.

[14] Ahmed, N., Natarajan, T., Rao, K.R., ”Discrete cosine Transforms”, IEEE Trans.Computers, vol.c-23, jan.1974, pp.90-93

[15] Buccigrossi, R., Simoncelli, E.P., ”EPWIC:Embedded Predictive Wavelet image coder”

[16] Chan, Y.T., ”WaveletBasics”, KluwerAcademicPublishers, Norwell, MA 1995

[17] Mallat, S.G., ”A Theory for multiresolution signal Decomposition:TheWaveletRepresentation”, IEEETrans.PAMI, vol.11, no.7, july1989, pp.74-693.

[18] J.M.Shapiro, ”Embedded image coding using zero tree of wavelet coefficients”, IEEE Trans.on signal processing vol.41, 3445-3462, 1993.

[19] A.Said, W.A.Pearlman, ”A new, fast, and efficient image codec based on setpartitioning in hierarchical trees”, IEEE Trans.on circuits and Systems for Video Technology, vol.6, 243-250, 1996.

[20] Rao.K.R., Yip, p., ”Discrete Cosine Transforms-Algorithms, Advantages, Applications”, Academic Press, 1990.

[21] Malavar, h.s., ”SignalProcessing with Lapped Transforms”, Norwood, MA, Artech House, 1992.