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A Performance Analysis of EZW, SPIHT Wavelet Based Compressed Images

C. Senthilkumar and R.K. Gnanamurthy
Department of ECE, Anna University, Chennai, India

Abstract: Image compression is the art and science of removing redundancies to represent information in a compact form. In this study, we have reviewed the performance of wavelet based compression techniques such as Embedded Zero Tree (EZW) and Set Partitioning In Hierarchical Tree (SPIHT). These methods combine stepwise thresholding and progressive quantization, focusing on more efficient way to encode the image coefficients in order to obtain better compression ratio. The redundancies are removed while the compression of image is coding, inter-pixel, psycho-visual and chromatic redundancies. The problems associated with image compression are aliasing, noise and artifacts. Lossless Compression algorithms preserve information and the compression process incurs no data loss but lossy compressions incur a loss of information. The applications of image compression are videoconferencing, satellite imaging, medical imaging, image transmission in internet, etc. The image parameters including file size, MSE, BPP and PSNR values of different wavelets are analyzed and results were discussed.

Key words: Compression, redundancy, wavelets, EZW, SPIHT, thresholding

INTRODUCTION

Image requires a lot of space as image files can be large. They also need to be exchanged among various systems imaging systems. This leads us to the area of image compression. Data compression algorithms are used in those standards to reduce the number of bits required to represent an image or a video sequence (Krahmer and Ward, 2014). Existing Discrete Cosine Transform (DCT) based compression algorithms such as those defined under the JPEG standard are very efficient in their memory utilization because, if needed, they can operate on individual image blocks (Kumar and Reddy, 2012; Khalifa, 2003; Jarske *et al*., 1994). In recent years, much of the research activities in image coding have been focused on the discrete wavelet transform. While the good results obtained by wavelet coders, e.g., the Embedded Zero tree Wavelet (EZW) coder (Khalifa, 2003) and the Set Partitioning in Hierarchical Trees (SPIHT) coder (Meier *et al*., 1999) are partly attributable to the wavelet transform. Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art or comics. This is because lossy compression methods (Chang *et al*., 2000; Martin and Bell, 2001; Kim *et al*., 2000; Usevitch, 2001) especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in bit rate.

WAVELETS

A wavelet is a wave like oscillation with small amplitude that starts out at zero, increases and then decreases back to zero. Wavelets (Chrysafis and Ortega, 2000; Shapiro, 1993; Li *et al*., 2001) are useful in wavelet based Compression and Decompression algorithms where it is desirable to recover the original information with minimal loss (Xiong *et al*., 1999).

Continuous Wavelet Transform (CWT): The continuous wavelet transform is the sum over all time of scaled and shifted versions of the mother wavelet ψ. Calculating the CWT (Khalifa, 2003) results in many coefficients C which are functions of scale and translation. The translation, τ is proportional to time information and the scale, s is proportional to the inverse of the frequency information.

Discrete Wavelet Transform (DWT): The DWT provides sufficient information for the analysis and synthesis of a signal but is advantageously, much more efficient. Discrete wavelet analysis (Chrysafis and Ortega, 2000; Li *et al*., 2001) is computed using the concept of filter banks. Resolution is changed by the filtering (Yoo *et al*., 1999; Marpe *et al*., 2000), the scale is changed by up sampling and down sampling. If a signal is put through two filters:

- A high pass filter, high frequency information is kept, low frequency information is lost
- A low pass filter, low frequency information is kept, high frequency information is lost

Corresponding Author: C. Senthilkumar, Department of ECE, Anna University, Chennai, India

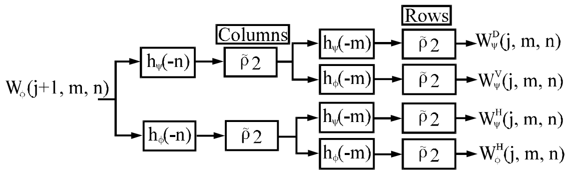

Fig. 1: Two dimensional DWT (decomposition)

Then, the signal is effectively decomposed into two parts, a detailed part (high frequency) and an approximation part (low frequency). The sub-signal produced from the low filter will have a highest frequency equal to half that of the original (Fig. 1).

IMAGE CODING METHODS

The image coding is that each successive bit of the bit stream that is received reduces the distortion of the reconstructed image by a certain amount. Embedded coding (Chang *et al*., 2000; Johnstone and Silverman, 1997; Kim *et al*., 2000) supports progressive image transmission by bit stream in their relative order. The mostly used image coders in wavelets are as follows:

Embedded Zero Tree Wavelet (EZW): An EZW encoder is specially designed to use with wavelet transforms. This means that when more bits are added to the stream, the decoded image will contain more detail.

Every wavelet coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. Zero Tree Root (ZTR) (Usevitch, 2001; De Vore *et al*., 1992) is a low scale "zero-valued" coefficient for which all the related higher-scale coefficients are also "zero-valued". Specifying a ZTR (Bajaj *et al*., 2001) allows the decoder to "track down" and zero out all the related higher-scale coefficients. It is a Lossy Image Compression algorithm (Yoo *et al*., 1999). At low bit rates, i.e., high compression ratios, most of the coefficients produced by a subband transform such as the wavelet transform will be zero or very close to zero. This occurs because "real world" images tend to contain mostly low frequency information highly correlated. However, where high frequency information does occur such as edges in the image, this is particularly important in terms of human perception of the image quality and thus must be represented accurately in any high quality coding scheme (Fig. 2).

EZW uses four symbols to represent, a zero tree root, an isolated zero (a coefficient which is insignificant but which has significant descendants), a significant positive coefficient and a significant negative coefficient. The symbols may be thus represented by two binary bits. The

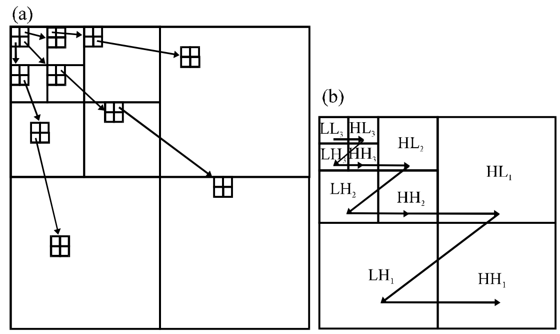

Fig. 2: EZW coding: a) EZW tree and b) scanning order

Fig. 3: Wavelet decomposition (I and II stage)

Compression algorithm (Deever and Hemami, 2003; De Vore *et al*., 1992; Bajaj *et al*., 2001) consists of a number of iterations through a dominant pass and a sub-ordinate pass, the threshold is updated (reduced by a factor of two) after each iteration. The dominant pass encodes the significance of the coefficients which have not yet been found significant in earlier iterations by scanning the trees and emitting one of the four symbols. The children of a coefficient are only scanned if the coefficient was found to be significant or if the coefficient was an isolated zero. The subordinate pass (Yoo *et al*., 1999; Pennebaker and Mitchell, 1993; Wallace, 1992) emits 1 bit (the most significant bit of each coefficient not so far emitted) for each coefficient which has been found significant in the previous significance passes. The sub-ordinate pass is therefore similar to bit-plane coding. The wavelet decomposition of the grayscale image in two stages are shown in Fig. 3.

Set Partitioning in Hierarchical Tree (SPIHT): SPIHT algorithm (Daubechies *et al*., 2003) provides partial ordering by magnitude with a Set Partitioning Sorting algorithm, ordered bit plane transmission and exploitation of self-similarity across different scales of an image wavelet transform. SPIHT provides a better performance than EZW. The SPIHT technique is based on three concepts:

- Partial ordering of the transformed image elements by magnitude with transmission of order by a Subset Partitioning algorithm that is duplicated at the decoder

- Ordered bit plane transmission of refinement bits
- Exploitation of the self-similarity of the image wavelet transform across different scales

The partial ordering is a result of comparison of transform element (coefficient) magnitudes to a set of octavely decreasing thresholds. Researchers say that an element is significant or insignificant with respect to a given threshold, depending on whether of not it exceeds that threshold. The crucial parts of coding process are that the way subsets of coefficients are partitioned and how the significance information is conveyed. The coding is actually done to the array:

$$c = \Omega(p)$$

Where:
Ω = A unitary hierarchical sub-band transformation
p = The original image

In a progressive transmission scheme, the decoder initially sets the reconstruction vector d to zero and updates its components according to the coded message. After receiving the value (approximate or exact) of some coefficients, the decoder can obtain a reconstructed image:

$$r = \Omega^{-1}(d)$$

SPIHT algorithm:

1. Actually, we need an algorithm that simply selects the coefficients such that $2^n \leq |c_{i,j}| \leq 2^{n+1}$ with n decremented in each pass.
2. Given n, if $|c_{i,j}| \geq 2^n$ then we say that a coefficient is significant; otherwise it is called insignificant.
3. The sorting algorithm divides the set of pixels into partitioning subsets τ_m and performs the magnitude test.
4. To reduce the number of magnitude comparisons (message bits), we define a set partitioning rule that uses an expected ordering in the hierarchy defined by the subband pyramid.
5. The objective is to create new partitions such that subsets expected to be insignificant contain a large number of elements and subsets expected to be significant contain only one element.
6. To make clear the relationship between magnitude comparisons and message bits, we use the function to indicate the significance of a set of coordinate's τ.

Two quantitative measures giving equivalent information are commonly used as a performance indicator for the compression. The compression ratio CR which means that the compressed image is stored using only CR of the initial storage size. The Bit-Per-Pixel ratio (BPP) which gives the number of bits required to store one pixel of the image. Two measures are commonly used to evaluate the perceptual quality. The Mean Square Error (MSE). It represents the mean squared error between the compressed and the original image. The lower the value of MSE, the lower the error. The Peak Signal to Noise Ratio (PSNR), represents a measure of the peak error and is expressed in decibels. The higher the PSNR, the better the quality of the compressed or reconstructed image. There are several things worth noting about these compressed images. First, they were all produced from one containing the 1 bpp compression of the Lena image. By specifying a bit budget, a certain bpp value up to 1, the SPIHT decompression program will stop decoding the 1 bpp compressed once the bit budget is exhausted. This illustrates the embedded nature of SPIHT (Pennebaker and Mitchell, 1993; Wallace, 1992). The compression of lena image by SPIHT algorithm as shown in Fig. 4.

Fig. 4: SPIHT compressions of Lena image; a) input image; b) SPIHT(8:1); c) SPIHT(16:1) and d) SPIHT(32:1)

Table 1: The EZW and SPIHT bsed compressed images with different waveles

Input images	Input file size	Wavelet	Comp. Method	MSE	PSNR	BPP	CR	Output file size (kb)
	48 kb	Haar	EZW	1.069	47.84	21.5808	89.92	20.9
		Db		1.069	47.84	21.5807	89.92	20.9
		Sym		1.169	47.45	21.1860	88.28	21.0
		Coif		1.150	47.52	21.1946	88.31	21.0
		Bior		1.069	47.84	21.5813	89.92	20.9
		Rbio		1.069	47.84	21.5813	89.92	20.9
		Dmey		1.170	47.45	21.1189	88.00	21.0
		Haar	SPIHT	19.060	35.33	10.1888	42.45	19.7
		Db		19.060	35.33	10.1887	42.45	19.7
		Sym		19.370	35.26	9.8649	41.10	19.9
		Coif		19.700	35.19	9.8542	41.06	19.9
		Bior		19.060	35.33	10.1892	42.46	19.7
		Rbio		19.060	35.33	10.1892	42.46	19.7
		Dmey		19.300	35.28	9.7058	40.44	19.9
	34.7 kb	Haar	EZW	7.693	39.27	8.4811	35.34	13.1
		Db		7.693	39.27	8.4811	35.34	13.1
		Sym		6.320	40.12	6.6194	27.58	13.3
		Coif		6.242	40.18	6.5197	27.17	13.2
		Bior		7.693	39.27	8.4817	35.34	13.1
		Rbio		7.693	39.27	8.4817	35.34	13.1
		Dmey		5.477	40.75	5.4788	22.83	13.2
		Haar	SPIHT	13.960	36.68	5.5291	23.04	12.4
		Db		13.960	36.68	5.5291	23.04	12.4
		Sym		11.250	37.62	4.2567	17.74	12.9
		Coif		12.580	37.13	4.1749	17.40	12.7
		Bior		13.960	36.68	5.5295	23.04	12.4
		Rbio		13.960	36.68	5.5295	23.04	12.4
		Dmey		9.637	38.29	3.4783	14.49	12.8

RESULTS

The EZW and SPIHT based compressed images with different wavelets are tabulated in Table 1. The results are showing that SPIHT based coding provides better compression rather EZW based coding. As a result the haar wavelets provides maximum compression and good Peak Signal to Noise Ratio (PSNR) and less Mean Square Error (MSE) than other wavelets.

CONCLUSION

In this study, we have reviewed the EZW and SPIHT based wavelet compression techniques. These methods provide better compression results than the existing techniques.

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