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Image Compression Using HAAR Wavelet Transform, DCT and Sub-Band Coding

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Abstract: **Image compression is a widely addressed researched area. Many compression standards are in place. But still here there is a scope for high compression with quality reconstruction. The introduction of the wavelets gave different dimensions to the compression. This paper aims at the analysis of compression using DCT and Wavelet transform The work is particularly targeted towards wavelet image compression using Haar Transformation with an idea to minimize the computational requirements by applying different compression thresholds for the wavelet coefficients and these results are obtained in fraction of seconds and thus to improve the quality of the reconstructed image. Using a simplified model of a subband coder, we explore key design issues. The role of smoothness and compact support of the basis elements in compression performance are addressed. We then look at the evolution of practical subband image coders.**

***Keywords:* Discrete Cosine Transform, Wavelet transform, subband coding, compression,**

1. INTRODUCTION

In the mid-1980's, wavelet theory was developed in applied mathematics. Soon, subband coding , which has been a very active research area for image and video compression, was identified as wavelet's discrete cousin. Furthermore, a fundamental insight into the structure of sub-band filters was developed from wavelet theory that led to a more productive approach to designing the filters. Thus subband and wavelet are often used interchangeably in the literature.

Two types of subband decomposition are commonly used in image compression, i.e., uniform and pyramidal decomposition. Uniform decomposition divides an image into equal-sized sub-bands (Fig. 1a). By contrast, pyramidal decomposition represents an octave-band (dyadic) decomposition, offering a multiresolution representation of the image as illustrated in (Fig. 1b). Most of the sub-band image coders published recently are based on pyramidal decomposition.

Conventional wavelet or subband image coders mainly exploit the energy compaction property of subband decomposition by using optimal bit allocation strategies. The drawback is apparent in that all zero-valued wavelet coefficients, which convey little information, must be represented and encoded, biting away a significant portion of the bit budget. Although this type of wavelet coders provide superior visual quality by eliminating the blocking effect in comparison to block-based image coders such as JPEG , their objective performance measured by peak signal-to-noise ratio (PSNR) increases only moderately.

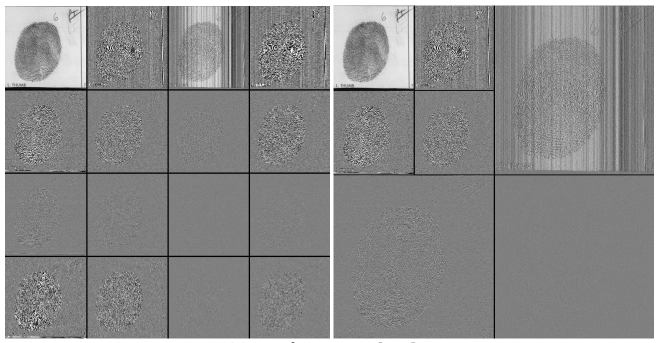

Figure 1: (a) Uniform wavelet decomposition
(b) Pyramidal wavelet decomposition

A fundamental issue in wavelet coding is: what is the statistical distribution of a wavelet-transformed image within or across subband when the image admits a stochastic model such as Markov random field? We will brief our initial exploration in this paper. Empirically, it has been observed that a wavelet-transformed image has the following statistical properties:

1. spatial-frequency localization,
2. energy compaction,
3. within-subband clustering of significant coefficients,
4. cross-subband similarity,
5. decaying of coefficients magnitudes across subband.

In recent years, we have seen an impressive advance in wavelet image coding. The success is mainly attributed to innovative strategies for data organization and representation of wavelet-transformed images which exploit the above statistical properties one way or the other. Three such top-ranked wavelet image coders have been published, namely,

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Shapiro's embedded zerotree wavelet coder (EZW) , Servetto et al.'s morphological representation of wavelet data (MRWD) , and Said and Pearlman's set partitioning in hierarchical trees (SPIHT) . Both EZW and SPIHT exploit cross-subband dependency of insignificant wavelet coefficients while MRWD does within-subband clustering of significant wavelet coefficients. As a result, the PSNR of reconstructed images is consistently raised by 1{3 dB over block-based transform coders.

2. IMAGE COMPRESSION

The need for image compression becomes apparent when number of bits per image are computed resulting from typical sampling rates and quantization methods. For example, the amount of storage required for given images is (i) a low resolution, TV quality, color video image which has 512 x 512 pixels/color,8 bits/pixel, and 3 colors approximately consists of 6 x 10^6 bits;(ii) a 24 x 36 mm negative photograph scanned at 12 x 10^{-6}mm:3000 x 2000 pixels/color, 8 bits/pixel, and 3 colors nearly contains 144 x 10^6 bits; (3) a 14 x 17 inch radiograph scanned at 70 x 10^{-6}mm: 5000 x 6000 pixels, 12 bits/pixel nearly contains 360 x 10^6 bits. Thus storage of even a few images could cause a problem. As another example of the need for image compression, consider the transmission of low resolution 512 x 512 x 8 bits/pixel x 3-color video image over telephone lines. Using a 96000 bauds (bits/sec) modem, the transmission would take approximately 11 minutes for just a single image, which is unacceptable for most applications.

2.1Types Of Compression Systems:

There are two types of compression systems
1.Lossy compression system 2.Lossless compression system
1.Lossy Compression System
Lossy compression techniques can be used in images where some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space.
2. Loss less compression system
Lossless Compression System which aim at minimizing the bit rate of the compressed output without any distortion of the image. The decompressed bit-stream is identical to original bit-stream.

2.2 DCT BASED CODING

The DCT based coding is the base for all image and video compression standards. In a DCT based system, the basic computing is the translation of an image block with a NxN dimension (in pixels), from the spatial domain in the DCT domain. In the compression standards, N=8. This number is chosen because, from an implementation point of view, an 8x8 image block does not need special requests of memory; moreover, algorithmic complexity for such a block is feasible on the most computing platforms. From the compression rate point of view, if we use an N bigger than 8, we will not obtain significant improvements.

2.3 WAVELET USED FOR IMAGE COMPRESSION

Wavelet theory had been developed independently on several fronts. Different signal processing techniques, developed for signal and image processing applications, had significant contribution in this development. Several families of wavelets that have proven to be especially useful are included in the wavelet toolbox. This paper has used three wavelets: Haar, Symlets and Bior wavelet for image compression. The details of haar wavelet Families have been shown below:

Haar Wavelets: Haar wavelet is the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1.

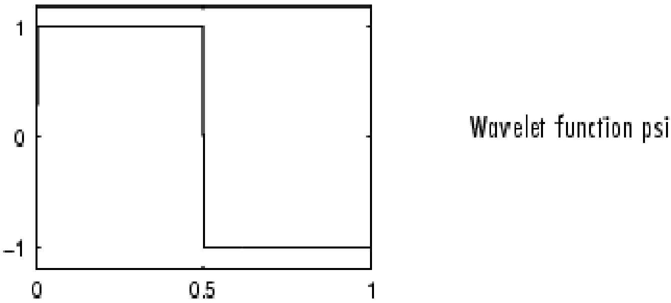

Fig: Haar Wavelet Function Waveform

3. DISCRETE COSINE TRANSFORM (DCT)

Data compression ratio, also known as compression power, is used to quantify the reduction in data-representation size produced by data compression . The data compression ratio is analogous to the physical compression ratio it is used to measure physical compression of substances, and is defined in the same way, as the ratio between the uncompressed size and the compressed size .

DCT is used because next reasons:

1. For high correlated data, the compression rate obtained by DCT is getting close to that obtained using the optimum Karhunen – Loeve transform.
2. DCT is an orthogonal transform. So, if in a matrix form, the DCT output is $Y=TXT^t$, then the inverse transform is $X=T^tYT$. The X→Y is named the direct DCT, and is given by,

$$Y_{kl} = \frac{c_k c_l}{4} \sum_{i=0}^{7} \sum_{j=0}^{7} x_{ij} \cos\left(\frac{(2i+1)k\pi}{16}\right) \cos\left(\frac{(2i+1)l\pi}{16}\right) \quad (1)$$

where k,1=0,…...7 & $c_{k=} \begin{cases} \frac{1}{\sqrt{2}}, & k=0 \\ 0 \end{cases}$

DCT can be written in matrix form, as *y=Tx*, where *x={x00,,…, x07,x10,…,x17,…, x77}*, and *T* is a matrix, whose elements are the products of the cosine functions defined before.
The inverse DCT transform can be written as:

$$x_{ij} = \sum_{k=0}^{7} \sum_{l=0}^{7} y_{kl} \frac{c_k c_l}{4} \cos\left(\frac{(2i+1)k\pi}{16}\right) \cos\left(\frac{(2j+1)l\pi}{16}\right) \quad (2)$$

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An important feature of 2-D DCT and of 2-D IDCT is separability. This means these 2 bidimensional transforms, written in matrix form, can be computed by performing 1-D DCT first on the rows, then on the columns of this matrix. The 1-D DCT is:

$$z_k = \frac{c(k)}{2} \sum_{i=0}^{7} x_i \cos\left(\frac{(2i+1)k\pi}{16}\right) \quad (3)$$

This equation can be written in matrix form as $z=TX$, where T is an 8x8 matrix, that have its elements equal to the cosine functions defined before; $x=\{x0,\ldots, x7\}$ is a row matrix, and z is a column matrix.

$$z_{il} = \frac{c(k)}{2} \sum_{j=0}^{7} x_{ij} \cos\left(\frac{(2j+1)l\pi}{16}\right) \quad (4)$$

the result of the 1-D DCT on xij rows. The previous equations suppose that the 2-D DCT can be obtained by performing the 1-D DCT on xij rows, then performing the 1-D DCT on zil columns. As matrix notation, $Y=TXT^{t}$ can be seen as $Z=TX^{t}$; $Y=TZ^{t}$. From an implementation point of view, this row-columns computing solution can simplify the hardware necessities, the price being an easy growth of the total number of performed operation.

4. WAVELET IMAGE CODING

Recent years have witnessed explosive growth in research activities involving wavelet image coding. Earlier related work in subband image coding showed the potential coding gain of subband/wavelet image coding, which depends on the spectrum flatness of the input image. An example of wavelet image coding is Shapiro's EZW coder. The main contribution of Shapiro work is zero tree quantization of wavelet coefficients, which works by efficiently predicting the children nodes based on the significance/insignificance of their parent. An embedded zero tree quantizer refines each input coefficient sequentially using a bitmap type of coding scheme, and it stops when the size of the encoded bit stream reaches the exact target bit rate.

Said and Pearlman described an SPIHT coder in that achieves about 1 dB gain in PSNR over Shapiro's original coder at the same bit rate for typical images (see Table).

The better performance of SPIHT coder is due to the following three reasons:

• Better wavelet filters (7/9 biorthogonal wavelet filters instead of length-9 QMF filters);
• special symbol for the significance/insignificance of child nodes of a significant parent;
• separation of the significance of child (direct descendant) nodes from that of the grandchild nodes.

TABLE .2
PERFORMANCE COMPARISON OF SHAPIRO'S EZW CODER [6] AND
THE SPIHT CODER [7] PROPOSED BY SAID AND PEARLMAN

	PSNR(DB)		
Rate	EZW(6)	SPIHT(7)	
(b/p)	lena Barbara	Lena	Barbara
0.125	30.23	31.09	24.85
0.25	24.03	34.11	27.58
0.5	33.17	37.21	31.39
0.75	26.77	39.04	34.25
1.00	36.28	40.40	36.41
	30.53		
	39.55		
	35.14		

DWT represents image on different resolution level i.e., it possesses the
Property of Multi-resolution. DWT [8]Converts an input image coefficients series x0,x1,xm into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

$$H_1 = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m(z)$$

(5)

$$L_1 = \sum_{m=0}^{k-1} x_{2i-m} \cdot t_m(z)$$

(6)

Where Sm (Z) and tm (Z) are called wavelet filters, K is the length of the filter, and i=0, [n/2]-1.In practice, such transformation will be applied recursively on the low-pass series until the desired number of iterations.

5. HAAR WAVELET TRANSFORM

Alfred Haar (1885-1933) was a Hungarian mathematician who worked in analysis studying orthogonal systems of functions, partial differential equations, Chebyshev approximations and linear inequalities. In 1909 Haar introduced the Haar wavelet theory. A Haar wavelet is the simplest type of wavelet . In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform..

The mathematical prerequisites will be kept to a minimum; indeed, the main concepts can be understood in terms of addition, subtraction and division by two. We also present a linear algebra implementation of the Haar wavelet transform, and mention important recent generalizations. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two sub signals of half its length.

The Haar wavelet transform has a number of advantages:

- It is conceptually simple and fast
- It is memory efficient, since it can be calculated in place without a temporary array.
- It is exactly reversible without the edge effects that are a problem with other wavelet transforms.

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- It provides high compression ratio and high PSNR (Peak signal to noise ratio).
- It increases detail in a recursive manner.

The Haar Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation. Data compression in multimedia applications has become more vital lately where compression methods are being rapidly developed to compress large data files such as images. Efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size.

Although the use of Wavelet Transforms was shown to be more superior to DCT when applied to image compression, some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space.

6. RESULTS AND DISCUSSIONS

In order to realize a compression process using Wavelet transform. The unwritten values are equal to zero. Each 8x8 image block is multiplicated with the transform matrix, the result being a matrix that is containing Wavelet coefficients.

The compression process is realized by quantizing the Wavelet coefficients matrix. Then, choosing a threshold value, all the coefficients that are smaller than this threshold are equalized to zero. It's obviously that the compression rate is depending on this threshold value, and also is the information loss.

For obtaining the compressed image, we have to apply the inverse Wavelet transform, that meaning to multiplicate the Wavelet coefficient matrix with the transpose of the matrix. Due to the losses, it can be seen some differences between the original image and the compressed one.

In figure 2, you can see the differences between the original image and the images compressed with that 2 methods.

Fig. 6. a) Original image
Fig. 6. b) Image compressed with DCT Compression rate 50%

Fig. 6. c) Image compressed with Wavelet transform Compressed rate 50%

The project deals with the implementation of the haar wavelet compression techniques and a comparison over various input images. We first look in to results of wavelet compression technique by calculating their compression ratios. Comparison between Haar and DCT for a sample image

	Compression Ratio	PSNR
Haar	99.5733%	-34.59
DCT	50%	-42.07

Table 2:comparision between Haar and DCT with respect to compression ratio

Figures given below gives the implementation of the haar wavelet compression techniques and a comparison over various input images. We first look in to results of wavelet compression technique by calculating their compression ratios.

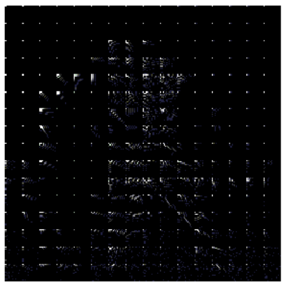

Fig 6.1.1:Original image using DCT
Fig 6.1.2:.compressed image using DCT

Fig 6.1.3:reconstructed image using DCT
Fig 6.2.1: original image using Haar wavelet transform

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Fig 6.2.2: reconstructed image for decomposition level 2

Fig 6.2.3: reconstructed image for decomposition level 3

Fig 6.3.1: original image using subband coding

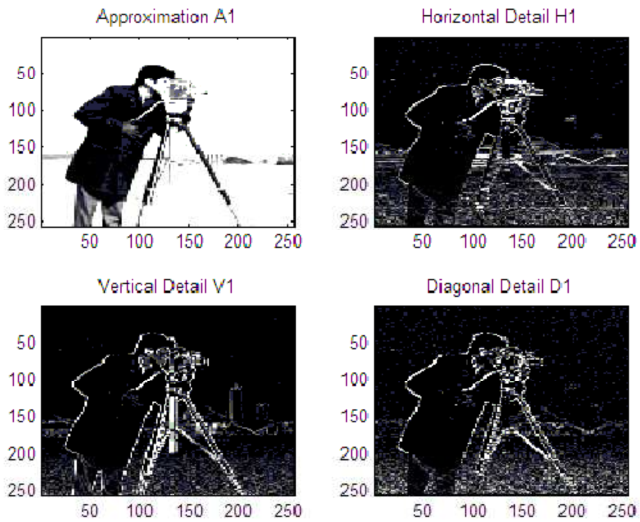

Fig 6.3.2: frequency level and edge detection with compression for level 1

Fig 6.3.3: reconstructed image for decomposition level 1

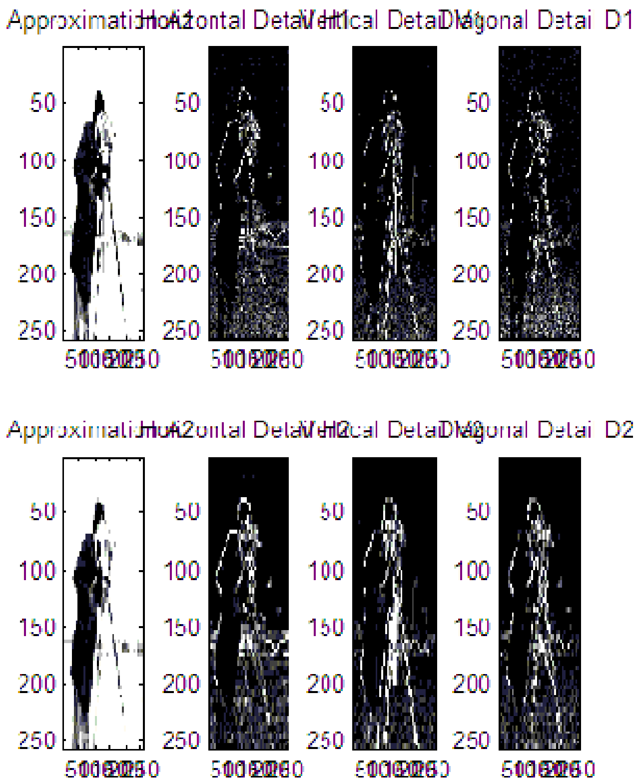

Fig 6.3.4: frequency level and edge detection with compression for level 2

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Fig 6.3.5: reconstructed image for decomposition level 2

CONCLUSION

This paper reported is aimed at developing computationally efficient and effective algorithm for lossy image compression using wavelet techniques. From above observations it is realized that compression ratio and PSNR got by Haar wavelet is more than that of DCT. Greater PSNR gives better picture quality. Along with Haar wavelets, we get adaptively quantized with a high frequency subband with greater resolution. These two compression techniques give well structured directional edges due to separable wavelets filters and large homogenous regions due to clustering with spatial constraints. Subband coding gives much lower bit rate than the original subband images.

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