Performance Analysis of Hybrid Multilevel DWT Coding for Optimum Quantization Factor Determination

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Abstract: ***Image compression defines as reducing the amount of data required to represent digital image. This paper describes a hybrid approach of image compression technique by combining discrete wavelet transform and discrete cosine Transform together for obtaining high quality image suitable for storage applications. We have used a wavelet base image coding that utilizes benefits of discrete cosine transform on specific sub bands of wavelet and compared the effects of wavelet analysis and representation , compression ratio, image content and resolution to image quality. We enhanced our hybrid approach by the addition of Huffman coding. Subjective and objective evaluation of image has been performed by using peak signal to noise ratio and compression ratio.***

Keywords: Cosine transform, Huffman Coding, Wavelet, Image compression,quantization

1. Introduction

In recent years, many studies have been performed on wavelets. An excellent overview of what wavelets have brought to the fields as diverse as biomedical applications, wireless communications, computer graphics or turbulence, is given in [1]. Image compression is one of the most dominant applications of wavelets. The fast increase in the range and use of electronic imaging justifies attention for systematic design of an image compression system and for providing the image quality needed in different applications.

A typical still image contains a large amount of spatial redundancy (extended information content) in plain areas where adjacent picture elements (pixels, pels) have almost the same values. It means that the pixel values are highly correlated [2]. In addition, a still image can contain subjective redundancy, which is determined by properties of an YCbCr [3]. An YCbCr presents some tolerance to distortion, depending upon the image content and viewing conditions. Consequently, pixels must not always be reproduced exactly as original image and the YCbCr will not detect the difference between original image and reproduced image. The redundancy (both statistical and subjective) can be removed to achieve compression of the image data. The basic measure for the performance of a compression algorithm is compression ratio (CR), defined as a ratio between original data size and compressed data size. In a lossy compression scheme, the image compression algorithm should attain a trade off between compression ratio and image quality [4]. Higher compression ratios will produce lower image quality and vice versa. Quality and compression can also vary as according to input image characteristics and contents.

2. Transform Coding Based Image Compression

Transform coding is a widely used method of compressing image information. In a transform-based compression system two-dimensional (2-D) images are transformed from the spatial domain to the frequency domain. A powerful transform will concentrate useful information into a few of the low-frequency transform coefficients. An YCbCr is more sensitive to energy with low spatial frequency than with high spatial frequency. Therefore, compression can be achieved by quantizing the coefficients, so that important coefficients (low-frequency coefficients) are transmitted and the remaining coefficients are discarded. Very productive and popular ways to achieve compression of image data are based on the discrete cosine transform (DCT) and discrete wavelet transform (DWT).

Current for compression of still (e.g., JPEG [5]) and moving images (e.g., MPEG-1 [6], MPEG-2 [7]) use DCT, which represents an image as a superposition of cosine functions with different discrete frequencies [8]. The transformed signal is a function of two spatial dimensions, and its parts are called DCT coefficients or spatial frequencies. DCT coefficients measure the contribution of the cosine functions at different discrete frequencies. DCT provides excellent energy compaction, and a number of fast algorithms exist for calculating the DCT. Most existing compression systems use square DCT blocks of regular size [5]–[7]. The image is divided into blocks NXN of samples and each block is transformed independently to give NXN coefficients. For many blocks within the image, most of the DCT coefficients will be nearly zero. DCT alone does not give compression. To attain the compression, DCT coefficients should be quantized so that the near-zero coefficients are set to zero and the remaining coefficients are represented with reduced precision that is determined by quantizer scale. The quantization results in loss of information, but also in compression. Increasing the quantizer scale leads to coarser quantization, this gives high compression and reduces final image quality.

The use of uniformly sized blocks simplified the compression system, but it does not take into account the irregular shapes within real images. The block-based segmentation (edge) of source image is a fundamental limitation of the DCT-based compression system [9]. The degradation is known as the “blocking effect” [9] and it depends on block size. A bigger block leads to more efficient coding, but requires more computational analysis. Image distortion is less annoying for small than for large DCT blocks, but coding efficiency tends to suffer. Therefore, most existing systems use blocks of 8X8 or 16 X16 pixels as a compromise between coding efficiency and image quality.

In recent times, many of the research activities in image coding have been focused on the DWT, which has now become a standard tool in image compression applications because of their data reduction capacity [10]–[12]. In a wavelet compression system, the whole image is transformed and compressed as a single data object rather than block by block as in a DCT-based compression system. It permits a uniform distribution of compression error across the entire image. DWT offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies) that is well suited to the properties of an YCbCr. It can provide better image quality than DCT, mostly on a higher compression ratio [13]. However, the implementation of the DCT is less expensive than that of the DWT. For example, the better algorithm for 2-D 8x8 DCT requires only 54 multiplications [14], while the complexity of calculating the DWT depends on the length of wavelet filters.

3. Discrete Cosine Transform

With the character of discrete Fourier transform (DFT), discrete cosine transform (DCT) turn over the image edge to make the image transformed into the form of even function. It's one of the most usual linear transformations in digital signal process technology. Here two dimensional discrete cosine transform (2D-DCT) is defined as

$$F(jk) = a(j)a(k)\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} f(mn)\cos\left[\frac{(2m+1)j\pi}{2N}\right]\cos\left[\frac{(2n+1)k\pi}{2N}\right] \quad (1)$$

The corresponding inverse transformation (Whether 2DIDCT) is defined as

$$f(mn) = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} a(j)a(k)F(jk)\cos\left[\frac{(2m+1)j\pi}{2N}\right]\cos\left[\frac{(2n+1)k\pi}{2N}\right] \quad (2)$$

The 2D-DCT can not only concentrate the main information of original image into the smallest low frequency coefficient, but also it can cause the image blocking effect being the smallest, which can realize the good compromise between the information centralizing and the computing complication. So it obtains the large spreading application in the compression coding.

4. Scalar Quantization

The typical way to handle floating-point data is to do scalar quantization. This approach allows some hierarchal coding techniques to be used on the quantized data, but may be unacceptable due to the irreversible data loss [13]. It is a process of approximation and a good quantizer is one, which represents the original signal with minimum loss or distortion [14]. In this work an adaptive and simple quantization method was adopted, where the quantizer step size is changed for each wavelet level (Pass) by using the relation:

$$\beta = \beta\times\alpha^{i-1}$$

Where β is the quantizer step used to quantize the coefficients of the wavelet (high pass) sub bands belong to the first level (i=1), and α is the attenuation parameter (such that α<1), i the level (pass) number. The reason behind making α<1, is that the importance of wavelet coefficients increase with increase of sub-band level.

5. Discrete Wavelet Transform

One of the big outcomes for wavelet analysis was that perfect reconstruction filter banks could be formed using the coefficient sequences a_L (k) and a_H (k) (Fig. 2). The input sequence is convolved with high-pass (HPF) and low-pass (LPF) filters a_L (k) and a_H (k) and each result is down sampled by two, producing the transform signals x_H and x_L.

The mathematical conversion that affects synthesis is called inverse DWT. An efficient way to implement this scheme using filters was developed by Mallat [16]. DWT for an image as a 2-D signal can be derived from 1-D DWT. The easiest way for obtaining scaling and wavelet function for two dimensions is by multiplying two 1-D functions. The scaling function for 2-D DWT can be obtained by multiplying two 1-D scaling functions: $\phi(x, y) = \phi(x)\phi(y)$. For the 2-D case, there exist three wavelet functions that scan details in horizontal $\psi^{(I)}(x,y)=\psi(x)\psi(y)$, vertical $\psi^{(II)}(x,y)=\psi(x)\psi(y)$, and diagonal directions: $\psi^{(III)}(x,y)=\psi(x)\psi(y)$. This may be represented as a four-channel perfect reconstruction filter bank as shown in Fig. 1. The resulting four transform components consist of all possible combinations of high- and low-pass filtering in the two directions. There are three types of detail images for each resolution: horizontal (HL), vertical (LH), and diagonal (HH). The operations can be repeated on the low–low band using the second stage of identical filter bank. Thus, a typical 2-D DWT, used in image compression, will generate the hierarchical pyramidal structure shown in Fig. 3(b).

In the spatial domain, the image can be considered as a composition of information on a number of different scales. A wavelet transforms measures gray-level image variations at different scales. In the frequency domain, the contrast sensitivity function of the YCbCr depends on frequency and orientation of the details.

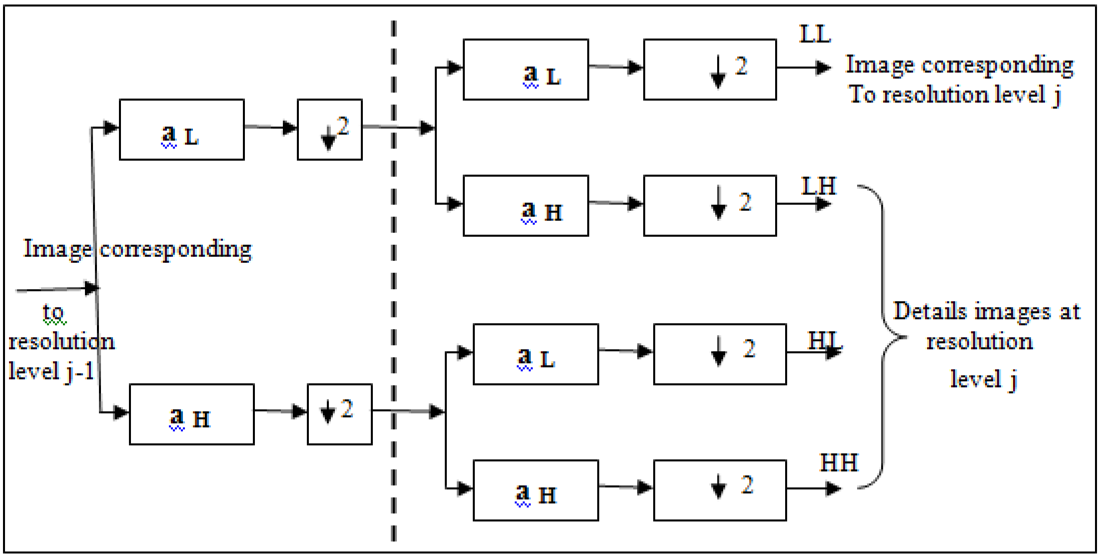


Figure 1: (a) one filter stage in 2-D DWT. (b) Pyramidal structure of a wavelet decomposition

6. Huffman Coding

This is the final step in the suggested compression scheme, where the output bit streams (produced in bit-slicing stage) will entropy coded. Many references introduce the basic idea of Huffman coding, thus in this paper the implementation of Huffman coding is based on the frequency of occurrence of each data item (pixel in images) [15]. The principle is to use a short codeword (lower number of bits) to encode the data that occurs more frequently. Codeword are stored in a codebook, which may be constructed for each image or a set of images. In all cases the codebook plus encoded data must be transmitted to enable decoding.

7. Proposed Approach

In our proposed image compression algorithm various steps are performed to apply image compression. The steps are given below with the flowchart of the proposed algorithm:

Step1: The image in an YCbCr color space is passed through 2D DWT operation.

Step2: LL, HL, LH and LL sub bands taken as DWT output (are of low significance).

Step3: HL and LH do not occupy much information are passed through the 2D DCT block processing.

Step4: The approximated component LL and HH represents high amount of data size and further compressed second time by 2d DWT decomposition (2 level of DWT) see figure 2. (4) DWT and DCT coefficients are further quantized.

Step5: Quantized coefficients are passed through Huffman coding algorithm to produce the compressed image data in encoded form.

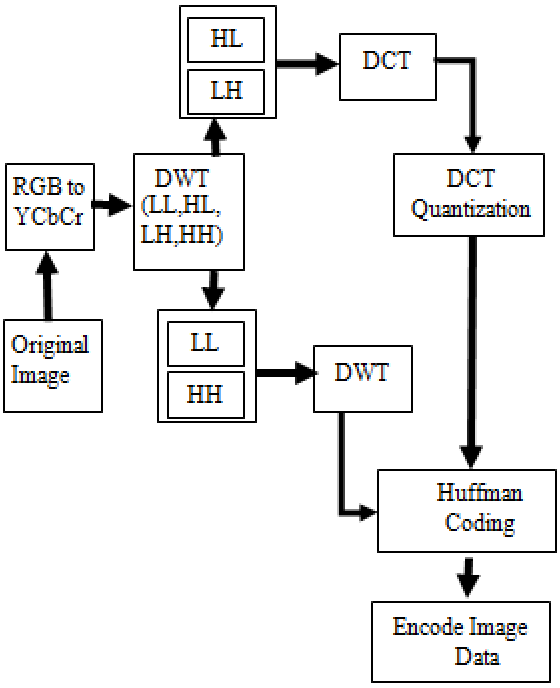


Figure 2: Coding process

8. Simulation Result

We have applied above discussed method for level 2 and level 3 compressions of office3.jpg and greens.jpg images. For each time we have changed the value of quantization factors of DCT and DWT matrices. For the DCT quantization factor (Q.F) there are three different types of Quantization factor which is named as Qy, Qcb and Qcr. We have taken Qcb and Qcr higher compared to Qy for maintaining quality of image by least possible losses of Y plane. The DCT Q.F are named as Q_{DCT}= [Qy Qcb Qcr] and DWT Quantization factor are named as Q_{DWT} there values are increase iteratively and PSNR and compression ratio is calculated for each time on both images for level two and level three compression.

A. Level 2 Compression

Figure 3 and 4 displays the decompressed image obtained after Level 2 compression and decompression at different value of Q_{dct} and Q_{dwt}. Figure 3(a to f) are recovered image for greens.jpg in this case we have found that as we increased Q.F. The image quality perceptually undistorted for fig 3 (a, b and c) but in fig 3 (d, e) the image colors and contrast becomes slightly dull. For figure 3(f) we can see that image has become distorted in a large amount but in perception and also information wise.

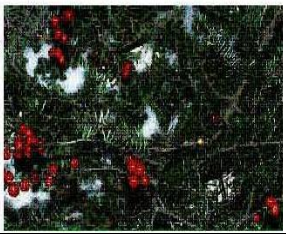
	
(a) Q_{dct}= [.05,.05,.05], Q_{dwt}=.005	(b)Q_{dct}=[.04,.05,.05], Q_{dwt}=.005
	
(c)Q_{dct}=[.08,.1,.1], Q_{dwt}=.005	(d) Q_{dct}=[.15,.2,.2], Q_{dwt}=.0.006
	
(e) Q_{dct}=[.3,.4,.4], Q_{dwt}=.0.007	(f) Q_{dct}=[.6,.8,.8], Q_{dwt}=0.008

Figure 3: Decompressed image for level 2 DWT DCT compression for greens.jpg image

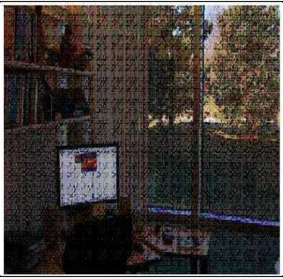
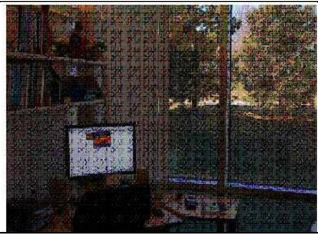
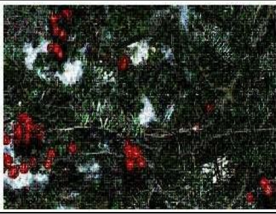
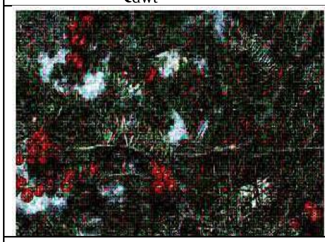
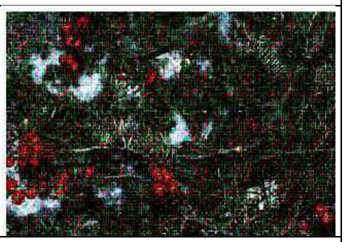
	
(a) Q_{dct}= [.05,.05,.05], Q_{dwt}=.005	(b)Q_{dct}=[.04,.05,.05], Q_{dwt}=.005
	
(c)Q_{dct}=[.08,.1,.1], Q_{dwt}=.005	(d) Q_{dct}=[.15,.2,.2], Q_{dwt}=.0.006
	
(e) Q_{dct}=[.3,.4,.4], Q_{dwt}=.0.007	(f) Q_{dct}=[.6,.8,.8], Q_{dwt}=0.008

Figure 4: Decompressed image for level 2 DWT DCT compression for office3.jpg image

B. Level 3 Compression

Figure 5 and 6 displays the decompressed image obtained after Level 3 compression and decompression at different value of Q_{dct} and Q_{dwt}. Figure 5(a to f) are recovered image for greens.jpg in this case we have found that as we increased Q.F. the image quality perceptually undistorted for fig 5 (a to d) in fig 5 (d) the image colors and contrast becomes slightly dull. For figure 5(f) we can see that image has become distorted due to compression losses.

Level3	
	
(a) Q_{dct}= [.05,.05,.05], Q_{dwt}=.005	(b)Q_{dct}=[.04,.05,.05], Q_{dwt}=.005
	
(c)Q_{dct}=[.08,.1,.1], Q_{dwt}=.005	(d) Q_{dct}=[.15,.2,.2], Q_{dwt}=.0.006
	
(e) Q_{dct}=[.3,.4,.4],	(f) Q_{dct}=[.6,.8,.8], Q_{dwt}=0.008

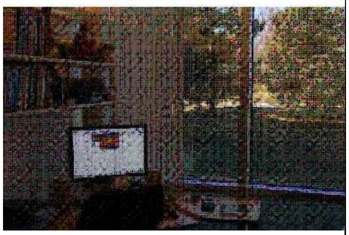
International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Q_{dwt}=.0.007	

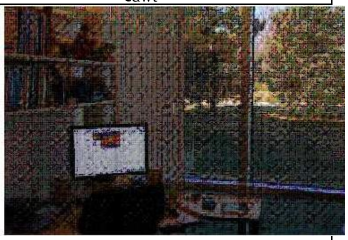
Figure 5: Decompressed image for level 3 DWT DCT compression for greens.jpg image.

(a) Q_{dct}= [.05,.05,.05], Q_{dwt}=.005

(b)Q_{dct}=[.04,.05,.05], Q_{dwt}=.005



(c)Q_{dct}=[.08,.1,.1], Q_{dwt}=.005



(d) Q_{dct}=[.15,.2,.2], Q_{dwt}=.0.006

(e) Q_{dct}=[.3,.4,.4], Q_{dwt}=.0.007

(f) Q_{dct}=[.6,.8,.8], Q_{dwt}=0.008

Table1: Image Name = greens.jpg

		Level 2		Level 3	
Qdct	**Qdwt**	**PSNR**	**C.R.**	**PSNR**	**C.R.**
.05,.05,.05	.05	30.4062	5.5432	29.4759	6.7461
.04,.05,.05	.05	30.4147	5.4255	29.6756	6.5484
.08,.1,.1	.005	30.3679	6.8159	29.4579	8.7147
.15,.2,.2	.006	30.2676	8.2193	29.3970	11.4106
.3,.4,.4	.007	30.1366	9.4717	28.8304	13.7195
.6,.8,.8	.008	28.8963	8.1668	28.7441	14.9726
.8,1,1	.01	28.8923	8.1532	28.7832	15.3025

Table1: Image Name = office.JPG

		Level 2		Level 3	
Qdct	**Qdwt**	**PSNR**	**C.R.**	**PSNR**	**C.R.**
.05,.05,.05	.05	35.3639	7.0150	33.0692	9.3844
.04,.05,.05	.05	35.3730	6.8032	33.0753	9.1210
.08,.1,.1	.005	30.6913	8.7217	30.8749	12.6482
.15,.2,.2	.006	30.6666	11.4526	30.8462	19.1423
.3,.4,.4	.007	30.6026	12.6223	31.0395	23.5248
.6,.8,.8	.008	30.2142	12.6964	29.9332	25.5709
.8,1,1	.01	30.2353	12.7870	29.9311	25.5836

9. Conclusion

In this paper we have shown an hybrid DWT-DCT algorithm that has been applied on two different images at different combination of quantization factor of DWT and DCT the results are tabulated in terms of PSNR and compression ratio for greens.jpg (Table 1) and office3.jpg (table 2) images for both level 1 and level 2 DWT transform. The main conclusion that are drawn from these tables are that as we increase the compression ratio (CR) increases for the greens.jpg the CR varies from 5 to 8 in level 2 and for level 3 it varies from 6 to 15 time but as the CR increases the PSNR is getting reduced near about from 30 to 28 for both levels. Similarly from office.jpg results analysis we can observe that in table 2 CR varies from 7 to 12 in level to and for level 3 it has range 6 to 15 .The PSNR varies for 35 to 30 approximately. For both level 2 and 3.However PSNR are acceptable for the cases having its value above than 33 for most of the decompressed image as seen in figure 3 to 6 for such cases the optimum Q_{dct} is $_{.05}$ and Q_{dwt} is.05 At the maximum compression ratio of 7. The above optimized value of Q.F can be further used to compress high quality biomedical images. We can also introduce more advanced DWT based compression and coding methods for getting higher CR.

10. Acknowledgment

The authors are thankful to Mr. Aseem Chauhan (Additional President, RBEF and Chancellor AUR, Jaipur), Maj. General K. K. Ohri (AVSM, Retd.) Pro-VC & Director General, Amity University, Uttar Pradesh Lucknow, Prof. S. T. H. Abidi (Director ASET, Lucknow Campus), Brig. U. K. Chopra (Director AIIT & Dy. Director ASET), Prof O. P. Singh (HOD, Electrical & Electronics) and Prof. N. Ram (Dy. Director ASET) for their motivation, kind cooperation, and suggestions.

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