Image Compression Using Discret Wavelet Transform

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Abstract

Image compression techniques are considered to be effective tools to reduce transmission bandwidth and the transmission cost of the image information or storage memory requirements. In this paper, we introduced image compression algorithm based on wavelet transform (WT) consider also effective tool, where we reduce non- significant high wavelets coefficients, these done by using block edge coding (BEC).The results give a good image quality with high compression ratios.

1 – Introduction

One of the modern methods for image compression is called wavelet encoding, which involves a discrete wavelet transforms on image and quantizing the wavelet coefficients by using suitable bit allocation schemes.

Wavelet–based compression schemes show much promise for the next generation of image compression method. It involves choosing scales and position based on powers of two, so called dyadic scales and position. The mother wavelet a rescaled or dilated, by powers of the two and translated by integer[1]. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. The signal is passed through a series of high passed filters to analyze the high frequencies, and it is passed through a series of low pass filter to analyze the low frequencies.

The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up sampling and down sampling (subsampling) operations. Subsampling a signal corresponds to reducing the sampling rate, or removing some of the signal samples. In DWT, an analysis filter bank followed by down sampleing produces the decomposition (analysis) of the image. The image is decomposed into sub-band correspond to higher image frequencies and other sub-band correspond to lower image frequency where the most of the image energy is concentrated.

2- Discrete Wavelet Transform :

An image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression [2]. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operation is then decimated by two. A two dimensional transform can be accomplished by performing two separate one-dimensional transforms. First, the image is filtering along the x dimension and decimated by two. Then, it is followed by filtering the sub-image along the y-dimension and decimated by two. Finally, we have split the image into four bands denoted by LL,LH,HL and HH after one-level decomposition. Further decomposition can be achieved by acting upon the LL subband successively and the resultant image is split into multiple bands as shown in figure (1).

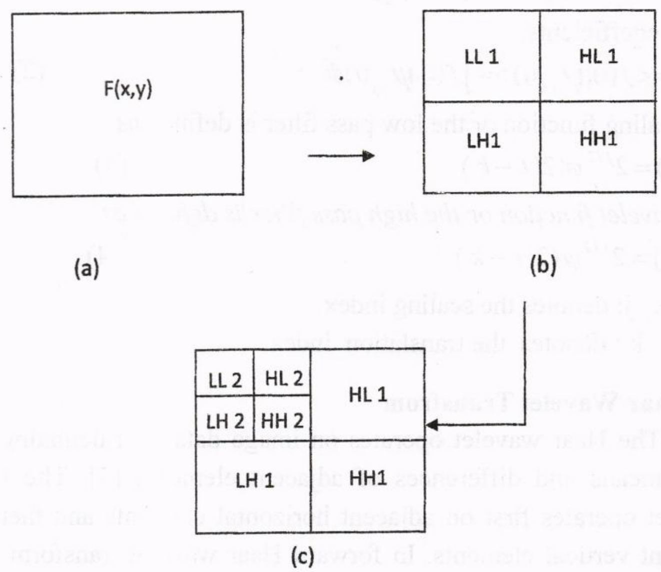


Figure (1) Two dimensional discrete wavelet transform

In mathematical terms [3], the averaging operation or low pass filtering is the inner product between the signal and the scaling function (ϕ) as shown in eq. (1) below. Whereas the differencing operation or high pass filtering is the inner product between the signal and the wavelet function (ψ) as shown in eq. (2) below [4].

Average coefficients,

$$C_j(K) = < f(t), \phi_{j,k}(t) > = \int f(t) . \phi_{j,k}(t) dt \qquad (1)$$

Detail coefficients,

$$d_j(k) = < f(t), \psi_{j,k}(t) > = \int f(t) . \psi_{j,k}(t) dt \qquad (2)$$

The scaling function or the low pass filter is defined as

$$\varphi_{j,k}(t) = 2^{j/2} \varphi(2^j t - k) \qquad (3)$$

The wavelet function or the high pass filter is defined as

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \qquad (4)$$

Where, j: denotes the scaling index.

k : denotes the translation index.

2-1 Haar Wavelet Transfrom

The Haar wavelet operates on image data by calculating the sums means and differences of adjacent elements [5]. The Haar wavelet operates first on adjacent horizontal elements and then on adjacent vertical elements. In forward Haar wavelet transform we divided image into blocks (2x2). Say (a, b, c and d) are the image pixel values, and apply Haar transform, we get new values (A, B, C and D) that are corresponding wavelet coefficients.

Where

$$A= (a+ b+c+d)* 0.25 \quad \text{------------------------------} \quad (5)$$

$$B= (a-b+c-d)*0.25 \quad \text{------------------------------} \quad (6)$$

$$C= (a+b-c-d)*0.25 \quad \text{------------------------------} \quad (7)$$

$$D= (a-b-c+d)*0.25 \quad \text{------------------------------} \quad (8)$$

In the inverse Haar wavelet transform we apply the following equations:

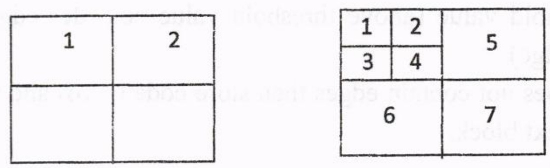
$$a= A+B+C+D \quad \text{------------------------------} \quad (9)$$

$$b= A-B+C-D \quad \text{------------------------------} \quad (10)$$

$$c= A+B-C-D \quad \text{------------------------------} \quad (11)$$

$$d=A-B-C+D \quad \text{------------------------------} \quad (12)$$

The following figure(2) showns one and two levels wavelet transforms



(a) One level DWT (b) Two levels DWT

Figure (2) Shows One and Two Levels Wavelet Transform

2-2 Encoding and decoding stages

Here we use Haar wavelet transform, and block edge coding (BEC) technique. Coding process is perfomed as

1- Input Image.

2- Perform WT (2-levels) for original image (get 7- subimages) see figure (2- b), get transform image (I)

3- Round integer the values of sub-image (1), and store it with (8-bits per element).

4- Put threshold values (5,10,...,25) to discrade high pass coefficients (in order to determine exits edge or not).

Block edges code (BEC), that is used to code sub-image coefficients (2-6), this is performed as follows:

i- Divide the sub-image into non-overlapping blocks (16x16).

ii-Determine, if the block contain edges or not through use threshold value (above threshold value consider edge other not edge) .

- If it does not contain edges then store code (zero) and move to the next block.

- Else for each point in block save two values:

One to save the position of the point (x,y), and the second value to represent the quantization value of this edge point by using :

$$q(r,c) = (ql * (I(r,c) + k)) / 255 \quad \text{----------- (13)}$$

Where

I(r,c)= Transform image (sub-image coefficients (2-6))

ql= maximum quantization value.

K= constant and in this work we take (K=128).

5- Ignoring transform coefficients in sub-image (7).

All these steps are shown in figure (3)

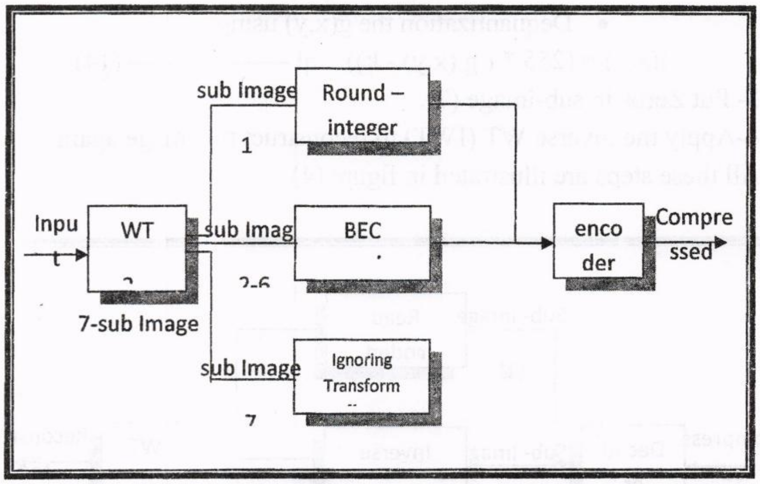


Figure (3)WT and BEC forward compression block

While the decoding process performed, see figure(4), by using the following steps:

1- Read first part from coded data file to reconstruct the low frequency band.

2- Perform inverse the block edge code to reconstruct the high frequency band as follows:-

a- Read code, if (code=0) then full the block (16*16) by zeros.

b- If ($code \neq 0$) then

- L = code (represent the location of the edge point in the block (i.e. (x,y)))
- Read next value (i.e.g(x,y))
- Dequantization the g(x,y) using:

$$I(x,y) = (255 * (g (x,y) - k)) / ql \quad (14)$$

3- Put Zeros in sub-image (7).

4-Apply the inverse WT (IWT) to reconstruct the image again.

All these steps are illustrated in figure (4)

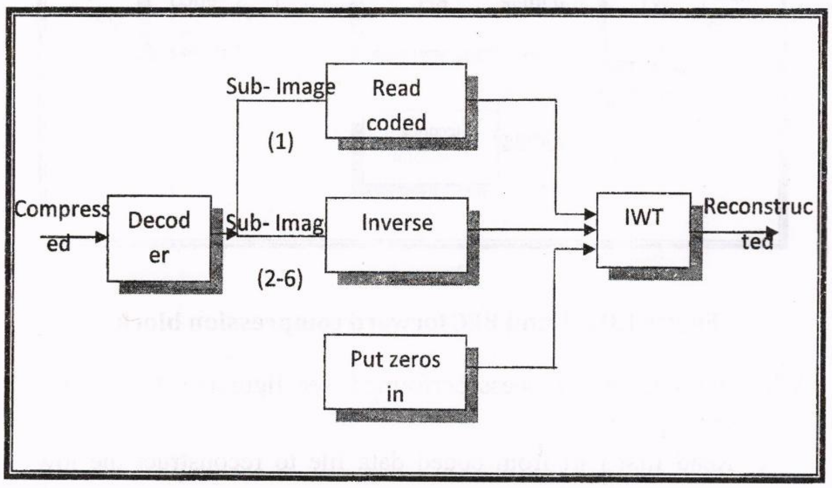


Figure (4) WT and BEC Decompression block diagram

3- Results and Discussion :

In this section, we shall discuss the results obtain by implementing the adopted image compression techniqueDiscrete wavelet transform

(DWT). In this section the threshold value is changed from (5,10,..,25), table (1) shows the test results, and figure (5) shows the resulted images by using this method, it is clear that the bit rate (B.R) will decrease (compression ratio (C.R) increases) with the increase of threshold value while the (peak signal- to noise Ratio(PSNR) value decreases with the increase in C.R value or (decreases in B.R).

Table (1) DWT coding technique results

Test image	**Size image**	**Threshold**	**B.R (bpp)**	**PSNR (db)**	**C.R**
FLOWER	256X256	5	1.821	34.19	4.3
		10	0.964	31.52	8.2
		15	0.72	30.075	11.1
		20	0.628	29.22	12.7
		25	0.58	28.60	13.7
Lena	256x256	5	2.38	35.252	3.3
		10	1.39	31.71	5.7
		15	0.97	29.30	8.3
		20	0.76	27.82	10.4
		25	0.64	26.78	12.5

Flowers 256x256, (8 bpp)

Threshold =25, PSNR =28.601, Br. = 0.58bpp

Lena 256x256, (8 bpp) Threshold =25 ,PSNR=26.78, B.r =0.649bpp

Figure (5) Reconstructed images from DWT coding technique

Reference

1- H.Olkkonen, " **Running Discrete Fourier Transform for time- Frequency analysis of Biomedical signals** ", Med. Eng. Phys, vo.17,no.6,1995.

2- Sheila Horan, "**Data Compression Statistic and Implication**" New Mexico State University, 2000.

3- Choo Li Tan, " **Still Image Compression Using Wavelet Transform**", Thesis, The University of Queensland 's School of Information Technology and Electrical Engineering, 2001.

4- Panrong Xiao,"**Image Compression By Wavelet Transform**" Msc.Thesis, East Tennessee state University, Department of computer and Information Sciences, 2001.

5- K. N. Ngan, K.S. Leong and H. Singh, "**Adaptive cosine transform coding of image in perceptual domain**", IEEE Trans. on ASSP, vol. 37, no. 11, November 1989.