Performance Analysis of SPIHT algorithm in Image Compression

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Abstract **In recent years there has been an astronomical increase in the usage of computers for a variety of tasks. With the advent of digital cameras, one of the most common uses has been the storage, manipulation, and transfer of digital images. The files that comprise these images, however, can be quite large and can quickly take up precious memory space on the computer's hard drive. In multimedia application, most of the images are in color. And color images contain lot of data redundancy and require a large amount of storage space. This project presents a new technique for compression of gray scale and color images using SPIHT algorithm along with wavelets. Compression can be done using different wavelets at different levels of decomposition. In this project the performance analysis of SPIHT with biorthogonal wavelets at four different levels of decomposition using EZW coding was presented. The technique performance of SPIHT compression is compared in terms of PSNR(Peak Signal to Noise Ratio), MSE(Mean Square Error), BPP(Bits per pixel), CR(Compression Ratio).**

Index Terms - ***SPIHT, Color Image, Wavelet, PSNR, MSE, BPP, CR***

I. INTRODUCTION:

In digital true color image, each color component that is R, G, B components, each contains 8 bit data[3]. Also color image contains lots of redundancy which will make it difficult to store and transmit. However, RGB [3] model is not suited for image processing purpose. For compression, a luminance-chrominance representation is considered due to superior to the RGB representation. Therefore, RGB images are transformed to one of the luminance-chrominance models, performing the compression process, and then transform back to RGB model because displays are most often provided output image with direct RGB model. The luminance component represents the intensity of the image and looks like a gray scale version. The chrominance components represent the color information in the image. The rest of the paper is organized as follows: Wavelet Transformation of Image is described in section II. SPIHT[1] algorithm is explained in section III. Modeling and results is

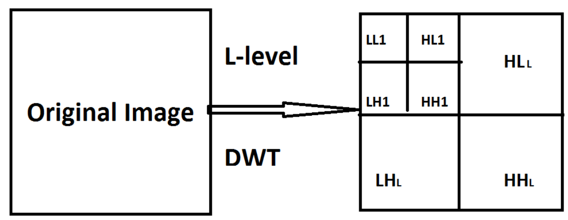

Fig.1 Wavelet Transform

given in section IV. Conclusion and Future work is explained in section V.

II.INTODUCTION TO WAVELET TRANSFORM

Wavelets[7] are mathematical functions that decompose data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods[4] in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction. The wavelet transformation[7] is a mathematical tool for decomposition.

Wavelet- based image compression is the order of the day as it enjoys several benefits. Primarily, it utilizes an unconditional basis function that decreases the size of the expansion coefficients to a negligible value as the index values increase. The wavelet expansion allows for a more precise and localized

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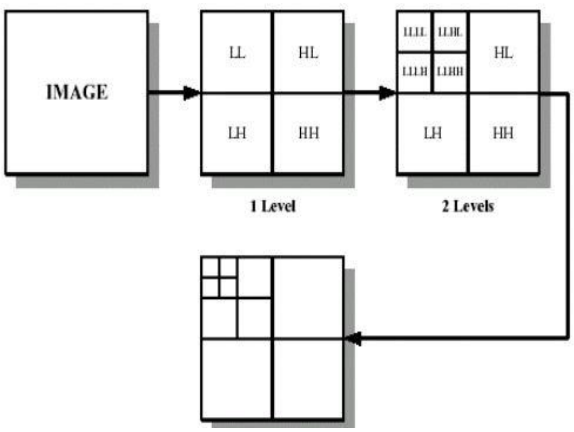
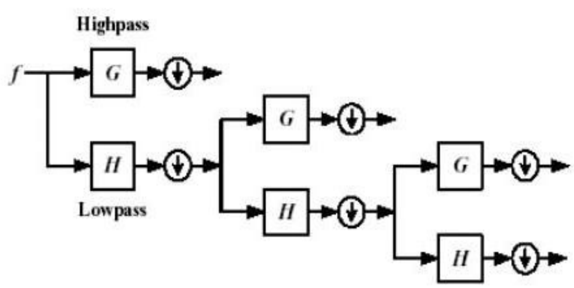
isolation and description of the signal characteristics. This ensures that DWT is very much effective in image compression applications. Secondly, the inherent flexibility in choosing a wavelet gives scope to design wavelets customized to fit individual requirements.

Wavelet analysis can thereby be used to represent the image in terms of two sub-signals. Firstly, the approximation sub-signal that captures the general trends in the image samples and the detail sub-signal that contains the high frequency vertical, horizontal and diagonal information



(a)



(b)

Fig 2: A Visual Representation of Three-level Decomposition using WT 34

In fig.2(a), In the first pass of the wavelet transform, LL represents the approximation coefficients while HL, LH and HH represent the three detail coefficients. Fig.2 (b) gives an alternative representation of the same procedure for three iterations of the wavelet transform, where G block outputs the high frequency information, H block retains the low frequency information and the ↓ indicates down sampling at every stage. It is seen that the DWT is computed by successive low pass and high pass filtering of the discrete samples. The down sampled output at the third level high pass filter contains the compressed image. Given below is a simple schematic to implement the DWT.

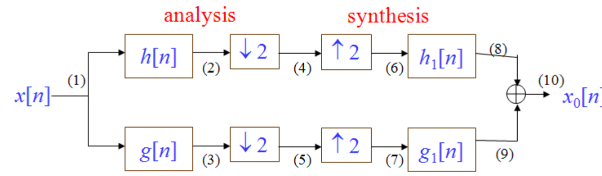


Fig 3: The Schematic Diagram to Realize DWT

III. INTRODUCTION TO SPHIT ALGORITHM:

The SPIHT[1] image coding algorithm was developed in 1996 by Said and Pearlman and is another more efficient implementation of the embedded zerotree wavelet (EZW)[2][8] algorithm by Shapiro. After the wavelet transform is applied to an image, the main algorithm works by partitioning the wavelet decomposed image into significant and insignificant partitions based on the following function:

$$S_n(T) = \begin{cases} 1, max_{(i,j)\in T}\{|c_{i,j}|\} > 2^n \\ 0, Otherwise \end{cases} \text{-->} \quad \textbf{(1)}$$

Where $S_n(T)$, is the significance of a set of co-ordinates T, and $c_{i,j}$ is the coefficient value at co-ordinate *(i,j)* . There are two passes in the algorithm - the sorting pass and the refinement pass. The sorting pass is performed on the list of insignificant sets (LIS), list of insignificant pixels (LIP) and the list of significant pixels (LSP). The LIP and LSP consist of nodes that contain single pixels, while the LIS contains nodes that have descendants. The maximum number of bits required to represent the largest coefficient in the spatial orientation tree is obtained and designated as n_{max}, which is

$$\mathbf{n_{max} = [\log_2(max_{i,j}\{|c_{i,j}|\})] \text{ --> } (2)}$$

During the sorting pass, those co-ordinates of the pixels which remain in the LIP are tested for significance by using eqn. 2. The result, *S,,(T),* is sent to the output. Those that are significant will be transferred to the LSP as well as having their sign bit output. Sets in the LIS (which consists of nodes with descendants will also have their significance tested and, if found to be significant, will be removed and partitioned into subsets. Subsets with a single coefficient and found to be significant will be added to the LSP,or else they will be added to the LIP. During the refinement pass, the nth most significant bit of the coefficients in the LSP is output. The value of *n* is decreased by 1 and the sorting and refinement passes are repeated. This continues until either the desired rate is reached or *n* =0, and all the nodes in the LSP have all their bits output. The latter case will result in almost perfect reconstruction as all the

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coefficients are processed completely. The bit rate can be controlled precisely in the SPIHT[1] algorithm because the output produced is in single bits and the algorithm can be terminated at any time. The decoding process follows the encoding exactly and is almost symmetrical in terms of processing time.

IV. PROPOSED IMAGE COMPRESSION TECHNIQUE USING SPIHT :

A. Block diagram:

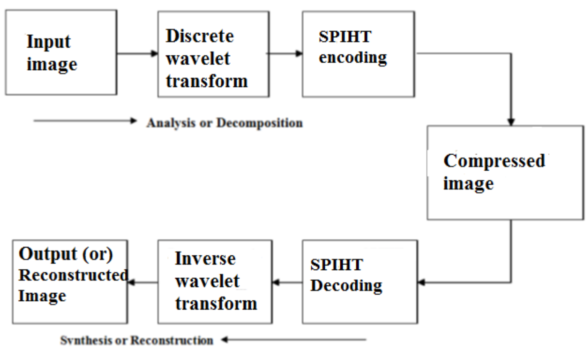

Fig. Block Diagram of Encoder &Decoder part of SPIHT Algorithm

B. DWT in Image compression

1) .Image content:

compression system is how to decide which test images to use for the evaluations. The image content being viewed influences the perception of quality irrespective of technical parameters of the system. In our simulation the main objective to test the larger set of wavelet functions, the test image considered is Lena 512x512, 8bpp. Choice of wavelet function is crucial for coding performance in image compression. However, this choice should be adjusted to image content The best way for choosing wavelet function is to select optimal basis for images with moderate spectral activity

2) Choice of Wavelet Function:

Important properties of wavelet functions in image compression applications are compactsupport ,symmetry , orthogonality , regularity, and degree of smoothness .In our experiment, five types of wavelet families are examined: Haar Wavelet (haarN), Daubechies Wavelet (dbN), Coiflet Wavelet (coifN), Symlet (symN)and Biorthogonal Wavelet (biorNdNr).Each wavelet family can be parameterized by integer that determines filter order (N). Biorthogonal wavelets can use filters with similar or dissimilar orders for decomposition (Nd) and reconstruction (Nr). In this simulation the results of Db1 is corresponds to haar transform

3) Filter order and Filter Length(J):

The filter length is determined by filter order, but relationship between filter order and filter length is different for different wavelet families. Higher filter orders give wider functions in the time domain with higher degree of smoothness. Filter with a high order can be designed to have good frequency localization, which increases the energy compaction. Wavelet smoothness also increases with its order. Filters with lower order have a better time localization and preserve important edge information. Wavelet-based image compression prefers smooth functions (that can be achieved using long filters) but complexity of calculating DWT increases by increasing the filter length. Therefore, in image compression application we have to find balance between filter length, degree of smoothness, and computational complexity. Inside each wavelet family (Bior1.1-Bior6.8), we can find wavelet function that represents optimal solution related to filter length and degree of smoothness, but this solution depends on image content.

4) Level of Decomposition(N):

The quality of compressed image depends on the number of decompositions (L). The number of decompositions determines the resolution of the lowest level in wavelet domain. If we use larger number of decompositions, we will be more successful in resolving important DWT coefficients from less important coefficients. After decomposing the image and representing it with wavelet coefficients, compression can be performed by ignoring all coefficients below some threshold. In our

experiment, CR is computed.

V. RESULTS & CONCLUSIONS:

1).Image Quality Evalution:

The image quality can be evaluated objectively and subjectively. Objective methods are based on computable distortion measures. A standard objective measure of image quality is MSE and PSNR. The reconstruction error E is given by

E = Original image - Reconstruction image

$$E = f(x,y) - \hat{f}(x,y) \quad \text{-------}\rightarrow(3)$$

$$MSE = E/\text{size of image } (N \times N) \quad \text{-------}\rightarrow(4)$$

A Standard objective measure of coded image quality is peak signal to noise ratio (PSNR) and is given by

$$PSNR = 20\log_{10}\left[\frac{255}{MSE}\right] \quad \text{------}\rightarrow(5)$$

Table 1.Performance analysis biorthogonal wavelets

for women image.

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S.no	Type of wavelet	M.S.E	P.S.N.R	B.P.P	Comp. Ratio(%)
1	Bior1.1	4.903	41.23	5.0336	62.92
2	Bior1.3	6.095	40.28	5.0883	63.60
3	Bior1.5	5.959	40.38	5.1147	63.93
4	Bior2.2	2.527	44.11	4.377	54.71
5	Bior2.4	2.247	44.61	4.3933	54.92
6	Bior2.6	4.528	41.57	4.4055	55.07
7	Bior2.8	3.563	42.61	4.4191	55.24
8	Bior3.1	4.366	41.73	4.1937	52.42
9	Bior3.3	3.182	43.10	4.1335	51.67
10	Bior3.5	3.274	42.98	4.1843	52.30
11	Bior3.7	3.477	42.72	4.1847	52.31
12	Bior3.9	3.745	42.40	4.1886	52.36
13	Bior4.4	4.385	41.71	4.3263	54.08
14	Bior5.5	10.85	37.77	4.4065	55.08
15	Bior6.8	4.06	42.05	4.3118	53.90

Table 1.Performance analysis biorthogonal wavelets for Lena color image.

S.no	Wavlet	M.S.E	P.S.N.R	B.P.P	C.r(%)
1	Bior1.1	3.016	43.34	10.0816	42.01
2	Bior1.3	2.884	43.53	10.0816	42.04
3	Bior1.5	3.021	43.33	10.119	42.13
4	Bior2.2	2.007	45.02	7.856	32.73
5	Bior2.4	1.883	45.50	7.9216	33.01
6	Bior2.6	1.852	45.45	7.0604	29.42
7	Bior2.8	1.942	45.25	7.094	29.56
8	Bior3.1	3.011	43.34	6.3328	29.39
9	Bior3.3	1.85	45.46	5.7309	23.88
10	Bior3.5	1.722	45.77	5.7228	23.84
11	Bior3.7	1.928	45.28	5.7321	23.88
12	Bior3.9	1.61	46.06	5.8857	24.52
13	Bior4.4	2.894	43.52	7.6105	31.71
14	Bior5.5	6.074	40.3	7.7573	32.32
15	Bior6.8	2.575	44.02	7.5914	31.33

2)Compression Ratio(CR):

It is defined as

Compression Ratio

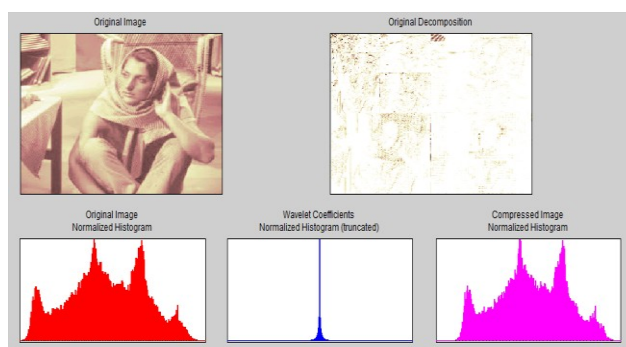
$$(CR) = \frac{\text{Image size before compression}}{\text{Image size after compression}}$$

$$= \frac{N1}{N2} \qquad \text{---------------}\rightarrow(6)$$

This expressed explicitly as N1:N2.

It is common to use the compression ratio at 4:1.The interpretation is that 4 pixels of the input image are expressed as 1 pixel in the output image.

3) Simulation results:



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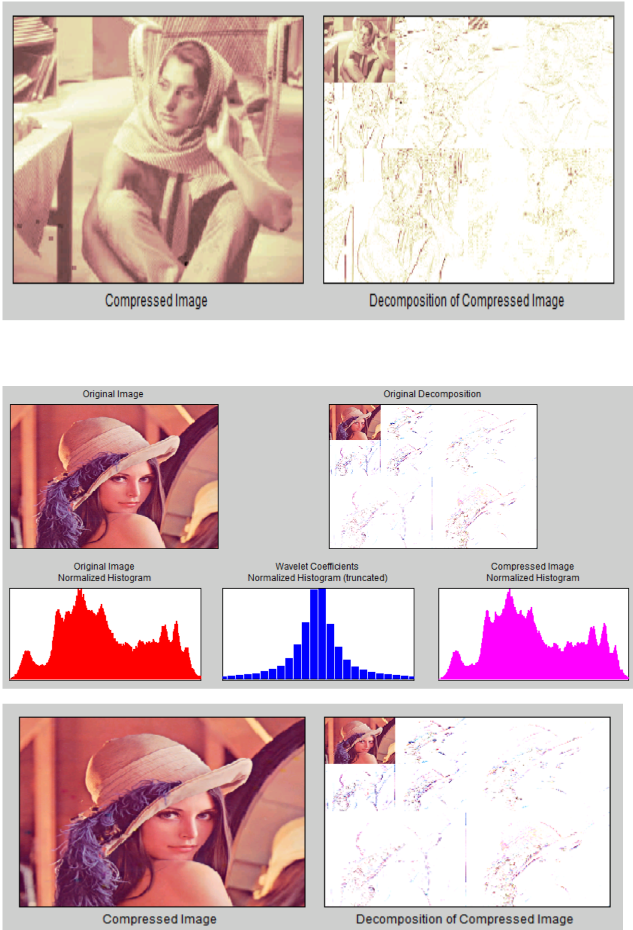

Fig.2 Simulation results for both color and grey scale images

The analysis which was been performed on the images and the performance measures are tabulated in the tables of different wavelets. Among all the wavelets Bi – Orthogonal wavelet performs well in both color and grey scale images. It was been observed that the performance is evaluated in terms of peak signal to noise ratio (PSNR),Mean Square Error(MSE),Bits per Pixel(BPP) and Compression Ratio(CR) with all types of wavelets , Among them biorthogonal wavelets is evaluated from 1.1 to 6.8.In that, bior 1.5 gives higher compression ratio i.e., 63.93% and bior 2.4 gives high PSNR i.e., 44.61 and less MSE 2.247 for the Woman (Grey Scale image).Also in Lena color image it was seen that in bior 1.1 to 6.8,bior 1.5 gives compression ratio i.e.,63.20% , bior 2.4 gives high PSNR i.e.,42.90 and less MSE 3.339..

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