PERFORMANCE ANALYSIS OF SET PARTITIONING IN HIERARCHICAL TREES (SPIHT) ALGORITHM FOR A FAMILY OF WAVELETS USED IN COLOR IMAGE COMPRESSION

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Abstract

With the spurt in the amount of data (Image, video, audio, speech, & text) available on the net, there is a huge demand for memory & bandwidth savings. One has to achieve this, by maintaining the quality & fidelity of the data acceptable to the end user. Wavelet transform is an important and practical tool for data compression. Set partitioning in hierarchal trees (SPIHT) is a widely used compression algorithm for wavelet transformed images. Among all wavelet transform and zero-tree quantization based image compression algorithms SPIHT has become the benchmark state-of-the-art algorithm because it is simple to implement & yields good results. In this paper we present a comparative study of various wavelet families for image compression with SPIHT algorithm. We have conducted experiments with Daubechies, Coiflet, Symlet, Bi-orthogonal, Reverse Bi-orthogonal and Demeyer wavelet types. The resulting image quality is measured objectively, using peak signal-to-noise ratio (PSNR), and subjectively, using perceived image quality (human visual perception, HVP for short). The resulting reduction in the image size is quantified by compression ratio (CR).

Keywords:

SPIHT, DWT, Image Compression

1. INTRODUCTION

Social networking and the always connected personal digital assistants (PDA) and more popularly called the smart phones paradigm have made a transformational impact on the real social lives of the connected world. As a consequence there is a huge burst in demand for image storage and transmission. Images and videos are uploaded and downloaded anytime, anywhere. Image storage and transmission is resource intensive, in such a scenario it is imperative to optimize storage and transmission bandwidth. Current popular method of compression is DCT [9],[10]. DCT based compression represents image as a superposition of cosine functions of different frequencies [11]. DCT is characterized by high speed and low cost and hence popular. DCT uses uniform sized square block size which reduces the complexity of compression. The uniform block size does not factor the irregular shape within the uniform block. This is the fundamental drawback of DCT which is known as blocking effect. Wavelets are extensively used due to their portability for image processing and particularly in image compression. Wavelets works on the principle of hierarchically decomposing an image into successful lower resolution components and their associated detailed components. At each level, the reference and detailed components contain the information required to reconstruct the reference component at the next higher resolution level. Wavelet provide good compression ratios and performed better when compared to popular techniques like JPEG in terms of signal to noise ratio and image quality. Unlike JPEG, it does not have blocking effect and allows for seamless degradation of the whole image quality. However the implementation complexity of wavelet based compression is higher than DCT. A study of the performance difference of the discrete cosine transform (DCT) and the wavelet transform for both image and video coding, was studied in the paper by Xiang et.al [8]. Performance analysis and comparison of wavelet families using for image compression of different images was studied in the paper [12]. This work attempts to perform an analysis of family of wavelets with the SPIHT algorithm for image compression. Wavelet [2],[3] is a small wave of limited duration, localized in time and scale and has an average value of zero. In recent times, much of the research activities in image coding have been focused on the discrete wavelet transform (DWT), which has become a standard tool in image compression applications because of their data reduction capability, low computational complexity, & possibility of constructing their own basis function [4],[5],[8]. In this paper, Daubechies, Coiflet, Symlet, Bi-orthogonal, Reverse Bi-orthogonal and Demeyer wavelet types are considered for image compression using SPIHT algorithm. Of most algorithms developed, SPIHT algorithm is treated as one of the most significant among these algorithms because it's fully embedded codec, optimized for progressive image transmission and provides good quality image and coding efficiency.

2. SPIHT ALGORITHM

SPIHT [7] was introduced by Said and Pearlman. The SPIHT algorithm is a highly refined version of the EZW [6] algorithm. The wavelet based SPIHT algorithm involves coding of the wavelet transform of an image by set partitioning along spatial orientation trees and progressive bit-plane coding of significant coefficients. The steps involved in the SPIHT algorithm are:

Step 1: Initialization.

The value of n is calculated to set threshold 2^n using the equation

$$n = \left\lfloor \log_2 \left(\max \left| c_{i,j} \right| \right) \right\rfloor \quad (1)$$

where, $c_{i,j}$ is the wavelet coefficient at co-ordinate (i, j). Three lists such as LSP (list of significant pixels), LIP (list of insignificant pixels) and LIS (list of insignificant set) are constructed. LSP is initialized as an empty set. LIP is initialized to contain all pixels in low pass sub band. LIS is initialized to contain all pixels in low pass sub band that have descendants and forms roots of spatial tree.

Step 2: Sorting pass.

The sorting pass is made for the first threshold. This pass involves checking the data several times and selecting coefficients such that $2n \leq | c(i, j) | \leq 2n+1$, with n being decremented at each pass. This pass divides the pixels into partitioning subsets and then tests each of these subsets for significant pixels. On finding that some pixels in the subset are significant, sorting pass divides subset into smaller subsets. This process continues until all the pixels in that subset are tested for significance.

Step 3: Refinement pass.

In refinement pass, the n^{th} MSB of all the coefficients found to be significant when compared with $2n+1$ are transmitted. These bits are transmitted in the same order as used to transmit the significance map during the sorting pass.

Step 4: Quantization-step update.

Decrement n by 1 and the procedure is repeated from step 2 onwards.

3. EXPERIMENT METHOD

The Fig.1 shows the steps involved. The experiment is conducted using MATLAB image processing tool. The color image used is the standard lena image, a 24 bit 256 × 256 .jpg image. The RGB color image is converted into YCbCr format. DWT is applied to each of YCbCr components. SPIHT algorithm is then applied to encode the DWT coefficients. A compressed image is created after this step. Entropy coding is avoided at this step for simplicity. In the next phase of decoding to obtain the reconstructed image, decoding is performed using SPIHT algorithm and inverse DWT is applied. YCbCr is later converted to RGB image. This experiment is repeated for different wavelet types and a range of coefficients for each of the wavelet types.

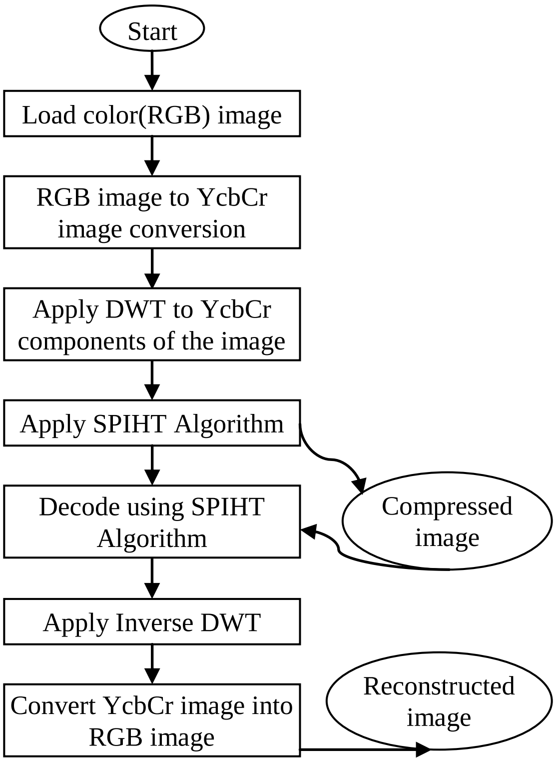

Fig.1. Color image processing using SPIHT algorithm

The performance is evaluated using PSNR, CR and HVP. For calculating PSNR, only Y (luminance) component of original and reconstructed image is used. Lena image shown in Fig.2 is used for our analysis. For computing HVP, ten individuals are asked to rate the quality of image on a scale of 1 to 5. The average of the rating of ten individuals is the HVP of that image.

Fig.2. Lena image

4. PERFORMANCE ANALYSIS PARAMETERS

We have used four different parameters to compare performance of the SPIHT algorithm in different wavelet families. The simplest and most widely used objective quality metric is the mean squared error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of peak signal-to-noise ratio (PSNR). We have used human visual perception (HVP) to evaluate the performance subjectively.

The MSE (mean square error) is

$$MSE = \left[\frac{1}{256 * 256} \sum_{x=0}^{255} \sum_{y=0}^{255} [h(x, y) - f(x, y)]^2 \right] \tag{2}$$

where, $h(x, y)$ is the original image matrix and $f(x, y)$ is the reconstructed image matrix.

The PSNR is defined as,

$$PSNR = 20 \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \tag{3}$$

where, MAX_I is the size of the image.

The amount of compression achieved is measured by the compression ratio (CR) defined as,

$$CR = \frac{Total\ number\ of\ bits\ in\ the\ original\ image}{Number\ of\ bits\ in\ the\ compressed\ image} \tag{4}$$

The HVP is evaluated by asking the individuals to identify the similarity between original and reconstructed images on a scale of 1 to 5.

5. RESULTS

A consistent method involving six steps was followed for performance analysis.

5.1 PERFORMANCE ANALYSIS STEPS

i. For the lena image, execute the algorithm by iterating over a range of wavelet coefficients for the chosen wavelet type.
ii. Plot PSNR and CR for the results obtained in step 1.
iii. Obtain the optimal wavelet coefficient. The optimal wavelet coefficient is one which has the highest CR and the corresponding PSNR. If the highest CR is the same for more than one coefficient, then choose the coefficient with the highest among the multiple highest CR.
iv. Repeat step 1, 2 and 3 for multiple family of wavelets. Fig.3 to Fig.7 depicts the charts used to determine the optimum wavelet coefficients for the chosen wavelet types.
v. Plot the PSNR and CR for each of the optimal coefficients determined from steps 1 to 4.
vi. From the plot in step 5, determine the best wavelet(s) and their corresponding coefficients.

The results are summarized in Table.1. For Daubechies, variation in CR and PSNR were negligible from db16 to db45 hence they were ignored Similarly, for Symlet, the coefficients from sym17 to sym37 were ignored.

Table.1. Summary of results

Wavelet = DB	**db1**	**db2**	**db3**	**db4**	**db5**	**db6**	**db7**	**db8**	**db9**	**db10**	**db11**	**db12**	**db13**	**db14**	**db15**
PSNR(db)	39.53	40.68	41.03	41.15	41.12	40.98	41.09	40.78	40.77	40.78	40.47	40.49	40.37	40.16	40.25
CR	1.82	1.09	1.08	1.074	1.067	1.0596	1.0596	1.053	1.046	1.053	1.0389	1.046	1.04	1.04	1.03
Wavelet = COIFLET	**coif1**	**coif2**	**coif3**	**coif4**	**coif5**										
PSNR(db)	40.82	41.31	41.36	41.28	41.23										
CR	1.09	1.09	1.08	1.074	1.067										
Wavelet = SYMLET	**sym2**	**sym3**	**sym4**	**sym5**	**sym6**	**sym7**	**sym8**	**sym9**	**sym10**	**sym11**	**sym12**	**sym13**	**sym14**	**sym15**	**sym16**
PSNR(db)	40.68	41.03	41.27	41.34	41.4	41.32	41.4	41.38	41.32	41.25	41.34	41.32	41.35	41.26	41.33
CR	1.09	1.08	1.08	1.09	1.074	1.074	1.074	1.074	1.067	1.067	1.067	1.067	1.059	1.059	1.059
Wavelet = BIOR	**bior1.1**	**bior1.3**	**bior1.5**	**bior2.2**	**bior2.4**	**bior2.6**	**bior2.8**	**bior3.1**	**bior3.3**	**bior3.5**	**bior3.7**	**bior3.9**	**bior4.4**	**bior5.5**	**bior6.8**
PSNR(db)	39.53	39.12	38.84	41.21	41.19	41.1	40.97	37.87	39.37	39.66	39.72	39.75	41.58	40.64	41.6
CR	1.84	1.7	1.67	1.11	1.103	1.095	1.095	1.0596	1.08	1.08	1.08	1.08	1.0958	1.067	1.088
Wavelet = RBIO	**rbio1.1**	**rbio1.3**	**rbio1.5**	**rbio2.2**	**rbio2.4**	**rbio2.6**	**rbio2.8**	**rbio3.1**	**rbio3.3**	**rbio3.5**	**rbio3.7**	**rbio3.9**	**rbio4.4**	**rbio5.5**	**rbio6.8**
PSNR(db)	39.53	41.16	41.09	38.05	39.45	39.69	39.74	28.86	34.01	36.09	36.79	36.97	40.54	40.5	40.95
CR	1.82	1.103	1.088	1.019	1.039	1.039	1.039	0.869	0.96	0.988	0.994	0.994	1.066	1.081	1.06
Wavelet = DMEY	**dmey**														
PSNR(db)	41.11														
CR	1.05														

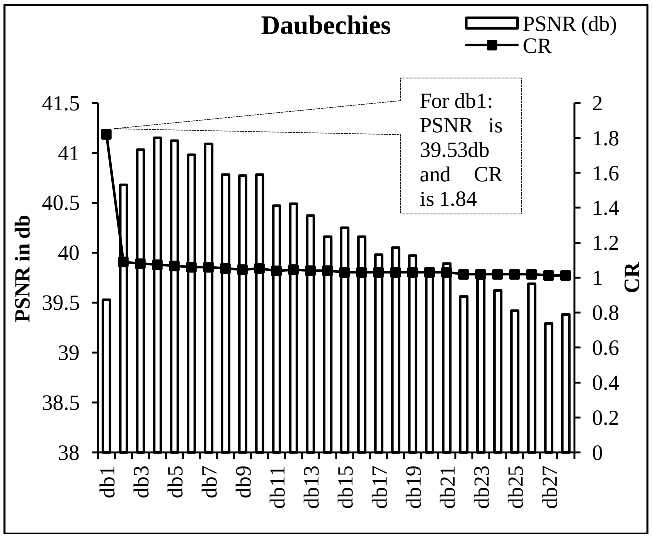

Fig.3. Optimum Daubechies (db) wavelet coefficient

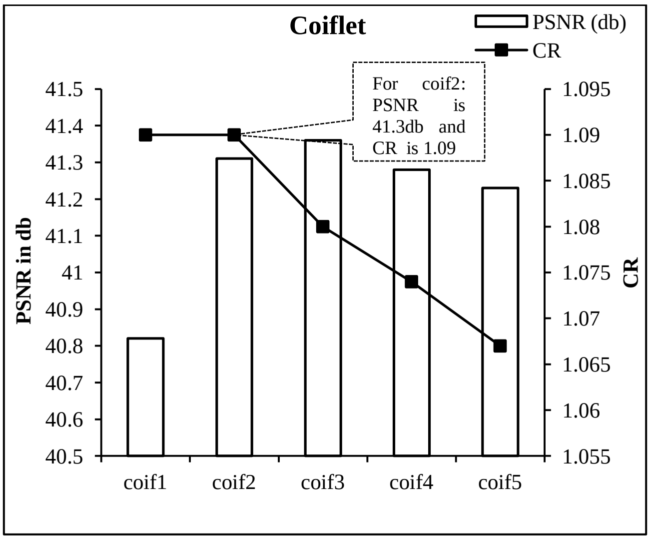

Fig.4. Optimum Coiflet (coif) wavelet coefficient

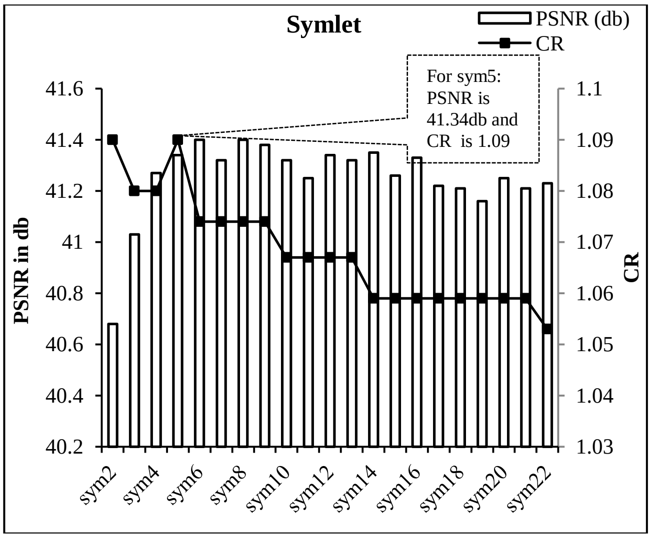

Fig.5. Optimum Symlet (sym) wavelet coefficient

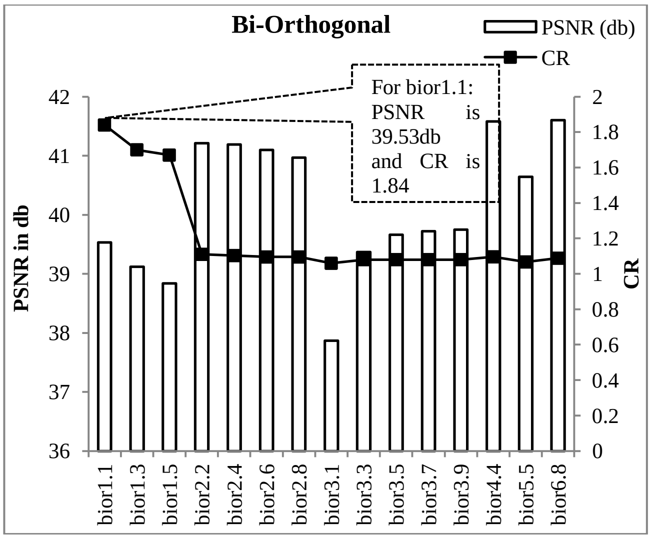

Fig.6. Optimum Bi-Orthogonal (bior) wavelet coefficient

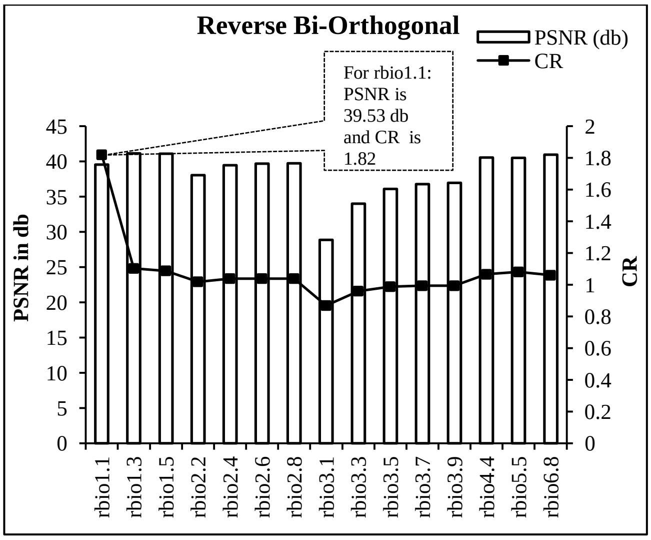

Fig.7. Optimum Reverse Bi-Orthogonal (rbio) wavelet coefficient

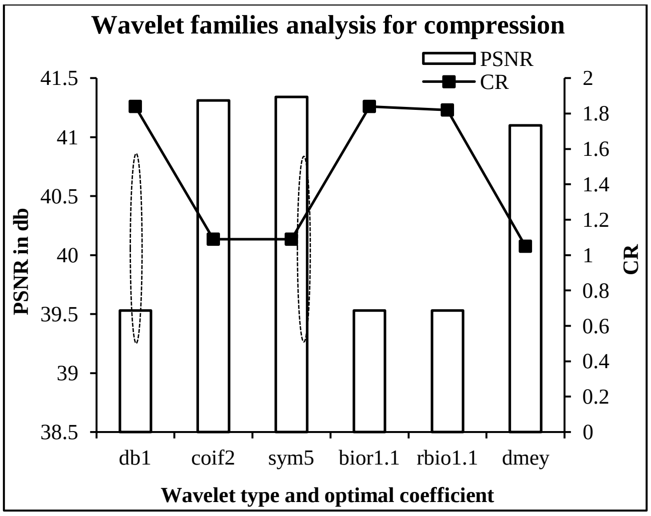

Fig.8. Determination of optimal performing wavelet

In Fig.3 to Fig.8, the PSNR is plotted as discrete values and CR as continuous values. The optimum wavelet coefficient for each wavelet type is determined from Fig.3 to Fig.7. The results are summarized in Table.2. Fig.8 is a plot of Table.2. From the Fig.8, it can be observed that the best performance is obtained for db1and bior1.1.

Table.2. Optimum wavelets coefficients

Wavelet Coefficient	db1	coif2	sym5	bior1.1	rbio1.1	dmey
PSNR	39.53	41.31	41.34	39.53	39.53	41.1
CR	1.84	1.09	1.09	1.84	1.82	1.05

5.2 OBSERVATION

Daubechies wavelet with coefficient db1 and Bi-Orthogonal with coefficient bior1.1 perform well on compression using SPIHT algorithm. For db1, a CR of 1.84 with PSNR of 39.53db is observed. For bior1.1, a CR of 1.84 with PSNR of 39.53db is observed. The Fig.9 and Fig.10 shows the results obtained by applying Daubechies (db1) and Bi-Orthogonal (bior1.1) wavelets to the original lena image.

Original Image Reconstructed Image

Fig.9. Lena compressed image obtained by applying db1 wavelet

Original Image Reconstructed Image

Fig.10. Lena compressed image obtained by applying bior1.1 wavelet

5.3 QUALITATIVE ASSESSMENT – TABULATION OF RESULTS

The reconstructed images chosen are obtained by applying Daubechies wavelet (db1) and Bi-Orthogonal wavelet (bior1.1) to the original image. Here original and reconstructed images are shown to ten individuals i.e., I1 to I10 and asked to rate similarity between original and reconstructed images in a scale of 1 to 5. The average of ten individual's ratings is calculated. Table.3 lists the HVP rating.

Table.3. HVP rating

Individuals	**l1**	**l2**	**l3**	**l4**	**l5**	**l6**	**l7**	**l8**	**l9**	**l10**
Rating-db1	4.9	4.8	4.7	4.8	4.7	4.7	4.7	4.9	4.9	4.9
Rating-bior1.1	4.8	4.9	4.8	4.7	4.8	4.7	4.8	4.9	4.9	4.9
Average rating, db1					4.8					
Average rating, bior1.1					4.82					

6. CONCLUSION

The most optimal performance of the algorithm is observed for Daubechies wavelet with coefficient db1 and Bi-orthogonal wavelet with coefficient bior1.1. A CR of 1.84 is observed at a PSNR of 39.53db for Daubechies wavelet (db1 coefficient) and CR of 1.84 with PSNR of 39.53db for Bi-Orthogonal (bior1.1 coefficient) wavelet.

7. FUTURE WORK

In this experiment a Lena JPEG image is considered for the analysis since the image has a moderate spectral activity. The experiment can be conducted for other standard images like cameraman, Zebra etc with varying spectral activity. The experiment was conducted on a low resolution image [24 bit 256 × 256]. This can be extended to high resolution images.

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