PERFORMANCE ANALYSIS OF IMAGE CODING USING WAVELETS

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Summary: The aim of this paper to examine a larger set of wavelet functions for implementation in a still image compression system using Set-Partitioning In Hierarchical Tree (SPIHT) algorithm. This paper discusses important features of wavelet transform in compression of still images, including the extent to which the quality of image is degraded by the process of wavelet compression and decompression. Image quality is measured objectively using peak signal to noise ratio. The effect of different parameters is studied on different wavelet functions.

Key words: Wavelet transform, image coding, Hierarchical Tree, peak signal to noise ratio.

1 Introduction

An image is a positive function on a plane. The value of this function at each point specifies the luminance or brightness of the picture at that point. Digital images are sampled versions of such functions, where the value of the function is specified only at discrete locations on the image plane, known as *pixels*. The value of the luminance at each pixel is represented to a pre-defined precision M. Eight bits of precision for luminance is common in imaging applications. The eight-bit precision is motivated by both the existing computer memory structures (1 byte = 8 bits) as well as the dynamic range of the human eye.

The prevalent custom is that the samples (pixels) reside on a rectangular lattice which we will assume for convenience to be $N \times N$. The brightness value at each pixel is a number between 0 and $2^M - 1$. The simplest binary representation of such an image is a list of the brightness values at each pixel, a list containing$N2M$ bits. Our standard image example in this paper is a square image with 512 pixels on a side. Each pixel value ranges from 0 to 255, so this canonical representation requires $5122 \times 8 = 2, 097, 152$ bits.

Image coding consists of mapping images to strings of binary digits. A good image coder is one that produces binary strings whose lengths are on average much smaller than the original canonical representation of the image. In many imaging applications, exact reproduction of the image bits is not necessary. In this case, one can perturb the image slightly to obtain a shorter representation. If this perturbation is much smaller than the blurring and noise introduced in the formation of the image in the first place, there is no point in using the more accurate representation. Such a coding procedure, where perturbations reduce storage requirements, is known as lossy coding. The goal of lossy coding is to reproduce a given image with minimum distortion, given some constraint on the total number of bits in the coded representation.

Wavelet transforms are arguably the most powerful, and most widely used tool to arise in the field of signal processing .Their inherent capacity for multiresolution representation akin to the operation of the human visual system (HVS) motivated a quick adoption and widespread use of wavelets in image-processing applications. Indeed, wavelet based algorithms (EZW, SPIHT)[1,2] have dominated image compression for over a decade , and wavelet-based source coding is now emerging in other domains. Wavelets are increasingly used in the source coding of remote-sensing, satellite, and other geospatial imagery.

A typical still image contains a large amount of spatial redundancy in plain areas where adjacent picture elements (pixels) have almost the same values. It means that the pixel values are highly correlated [3]. In addition, a still image can contain subjective redundancy, which is determined by properties of HVS. The redundancy can be removed to achieve compression of the image data. A basic measure for the performance of a compression algorithm is compression ratio (CR). Wavelet compression is a lossy compression scheme, the image compression algorithm should achieve a tradeoff between CR and image quality. Higher compression ratios will produce lower image quality and vice-versa.

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Quality and compression also vary according to input image characteristics and content.

Transform coding is a widely used method of compressing image information. In a transform –based compression system 2-D images are transformed from the spatial domain to the frequency domain. An effective transform will concentrate useful information into a few of the low-frequency transform coefficients. An HVS 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 as shown in fig.1. Very effective and popular way to achieve compression of image data is based on DWT used in JPEG2000 standard.

2 . Wavelet Transform Based Image Coding

TRANSFORM QUANTIZER
COMPRESSOR

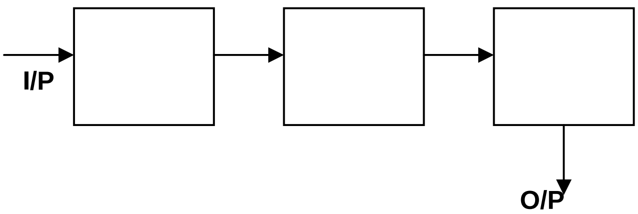

Fig.1 Wavelet based Coder

Fig.1 shows the wavelet based coder has three basic components: a transformation, a quantizer and data compression. Most existing high performance image coders in applications are transform based coders [4]. In the transform coder, the image pixels are
Converted from the spatial domain to the transform domain through a linear orthogonal or bi-orthogonal transform. A good choice of transform accomplishes a decorrelation of the pixels, while simultaneously providing a representation in which most of the energy is usually restricted to a few (relatively large) coefficients. This is the key to achieving an efficient coding (i.e., high compression ratio). Indeed, since most of the energy rests in a few large transform coefficients, we may adopt entropy coding schemes, e.g., run-level coding or bit plane coding schemes, that easily locate those coefficients and encodes them. Because the transform coefficients are highly decorrelated, the subsequent quantizer and entropy coder can ignore the correlation among the transform coefficients, and model them as independent random variables.

The optimal transform (in terms of decorrelation) of an image block can be derived through the Karhunen–Loeve (K-L) decomposition. Here we model the pixels as a set of statistically dependent random variables, and the K-L basis is that which achieves a diagonalization of the (empirically determined) covariance matrix. However, the K-L transform lacks an efficient algorithm, and the transform basis is content dependent.

Popular transforms adopted in image coding include block-based transforms, such as the DCT, and wavelet transforms. The DCT (used in JPEG) has many well-known efficient implementations and achieves good energy compaction as well as coefficient decorrelation. However, the DCT is calculated independently in spatially disjoint pixel blocks. Therefore, coding errors (i.e., lossy compression) can cause discontinuities between blocks, which in turn lead to annoying blocking artifacts. In contrary, the wavelet transform operates on the entire image (or a tile of a component in the case of large color image), which both gives better energy compaction than the DCT, and no post-coding blocking artifact. Moreover, the wavelet transform decomposes the image into an L-level dyadic wavelet pyramid. The output of an example 5-level dyadic wavelet pyramid is shown in Figure 2.

There is an obvious recursive structure generated by the following algorithm: low pass and high pass filters (explained below, but for the moment, assume that these are convolution operators) are applied independently to both the rows and columns of the image. The output of these filters is then organized into four new 2D arrays of one half the size (in each dimension), yielding a LL (low pass, low pass) block, LH (low pass, high pass), HL block and HH block. The algorithm is then applied recursively to the LL block, which is essentially a lower resolution or smoothed version of the original. The multiresolution nature of the wavelet transform is ideal for resolution scalability.

3. About EZW and SPIHT

The concept of lossy wavelet image coding based on trees was initially introduced in embedded zero-tree wavelet (EZW) coding [1], by Shapiro in 1993. Based on the zero-tree concept, if a wavelet coefficient at a given scale is found to be insignificant with respect to a given threshold, the 2 × 2 offspring of that coefficient at the next finer scale
is also assumed to be insignificant. Furthermore, the high frequency detail sub bands have been shown to have a

generalized Gaussian distribution centered on zero. This means that most of the coefficients in these sub bands have very small magnitudes and thus low energy. The zero-tree concept coupled with the fact that the detail sub bands contain only a few significant coefficients is exploited in EZW to give an efficient coding scheme.

The SPIHT algorithm, developed by Said and Pearlman in 1996 [2], is a fast and efficient image compression algorithm that works by testing ordered wavelet coefficients for significance in a decreasing bit plane order, and quantizing only the significant coefficients. The high coding efficiency obtained by this algorithm is due to a group testing of the coefficients that belong to a wavelet tree. Group testing is advantageous because of the inter-band correlation that exists between the coefficients belonging to a tree. The SPIHT uses the fundamental idea of zero-tree coding from the EZW but is able to obtain more efficient and better compression performance in most cases without having to use an arithmetic encoder. The SPIHT algorithm groups the wavelet coefficients and trees into sets based on their significance information. The encoding algorithm consists of two main stages, sorting and refinement. In the sorting stage, the threshold for significance is set as 2n, where n is the bit level, and its initial value is determined by the number of bits required to represent the wavelet coefficient with the maximum absolute value. Significance for trees is obtained by checking all the member detail coefficients. Approximation coefficients are tested as individual entries. The initial listing that determines the order in which significance tests are done is predetermined for both the approximation coefficients as well as the trees. The algorithm searches each tree, and partitions the tree into one of three lists: 1) the list of significant pixels (LSP) containing the coordinates of pixels found to be significant at the current threshold; 2) the list of insignificant pixels (LIP), with pixels that are not significant at the current threshold; and 3) the list of insignificant sets (LIS), which contain information about trees that have all the constituent entries to be insignificant at the current threshold.
If a coefficient or a tree is found to be insignificant, a “0” bit is sent to the output bit stream and the corresponding coordinates are moved to the LIP or LIS respectively, for subsequent testing at a lower bit level. When a coefficient is found to be significant, a “1” bit and a sign bit are sent out and its coordinate is moved to the LSP. If an LIS member is found to be significant, a “1” bit is sent out and the tree is partitioned into its offspring and descendants of offspring. The offspring are moved to the end of the LIP and subsequently tested for significance at the same bit level. The offspring are also moved to the LIS as the roots

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4. Image Quality Evaluation

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

$$E = \text{Original image} - \text{Reconstruction image} \qquad (1)$$

$$MSE = E \,/\, \text{size of image } (N \times N) \qquad (2)$$

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

$$PSNR = 20 \log_{10} \left(\frac{255}{MSE} \right) \qquad (3)$$

In this work, we considered only PSNR measure. The subjective measure of mean opinion score (MOS) or by picture quality scale (PQS) to be analyzed in the future work of study.

5. DWT In Image Coding

5.1 Image Content

The fundamental difficulty in testing an image 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 [3].

5.2 Choice of Wavelet Function

Important properties of wavelet functions in image compression applications are compact support ,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.

5.3. 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,(Db1-Db9), (Bior1.1-Bior6.8), (Sym1-Sym8), (Coif1-Coif5), we can find wavelet function that represents optimal solution related to filter length and degree of smoothness, but this solution depends on image content. Table- 1 show the test results for L=3, bpp=1 for different wavelet functions.

Table-1 Effect of wavelet filter order on PSNR (L=3, bpp=1)

Wavelet function	PSNR	Wavelet function	PSNR
Db1	37.49	Coif1	39.06
Db2	38.95	Coif2	39.68
Db3	39.45	Coif3	39.82
Db4	39.62	Coif4	39.84
Db5	39.69	Coif5	39.85
Db6	39.68	Sym1	37.49
Db7	39.71	Sym2	38.95
Db8	39.63	Sym3	39.45
Db9	39.66	Sym4	39.63
Bior1.1	37.49	Sym5	39.74
Bior2.2	39.24	Sym6	38.81
Bior4.4	39.85	Sym7	39.84
Bior5.5	39.48	Sym8	39.86
Bior6.8	39.92		

5.4. Level of Decompositions (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. image Lena (512x512 pixels, 8 bit/pixel) for 2, 3, 4 ,5and 6 decompositions .

The higher the decomposition level , the higher PSNR is obtained for a given bpp as shown in Table-2(a) and 2(b). As decomposition level increases the computational complexity also increases.

Table-2 Effect of level of decomposition (L),on CR L=3

CR	Db7	Db9	Bior2.2	Bior4.	Sym5	Coif5
4	41.54	40.97	41.39	41.62	41.54	41.64
8	35.66	34.03	35.66	35.78	35.68	35.83
10	33.10	31.00	33.15	33.21	33.15	33.32
20	24.79	21.27	25.95	24.58	24.82	24.88
40	21.39	10.93	17.70	16.25	16.59	16.58

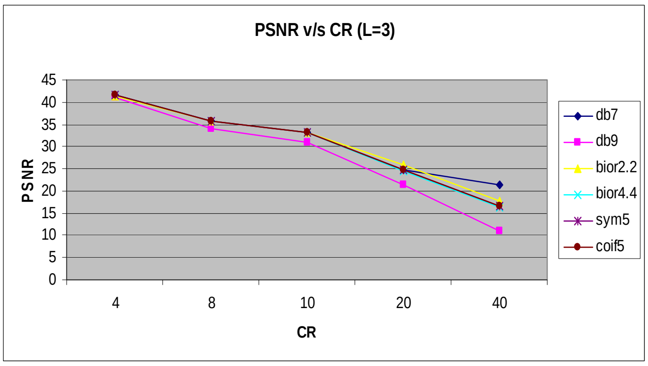

Fig. 2 PSNR V/S CR (L=3,FIXED)

Table-3 Effect of level of decomposition (L), CR=10:1

WFL	Db7	Db9	Bior22	Bior44	Sym5	Coif5
2	16.91	16.92	17.88	16.73	16.92	16.93
3	33.10	31.00	33.15	33.21	33.15	33.32
4	37.46	37.38	37.38	37.88	37.70	37.82
5	38.24	38.16	38.13	38.48	38.28	38.37
6	38.35	38.25	38.22	38.65	39.03	38.52

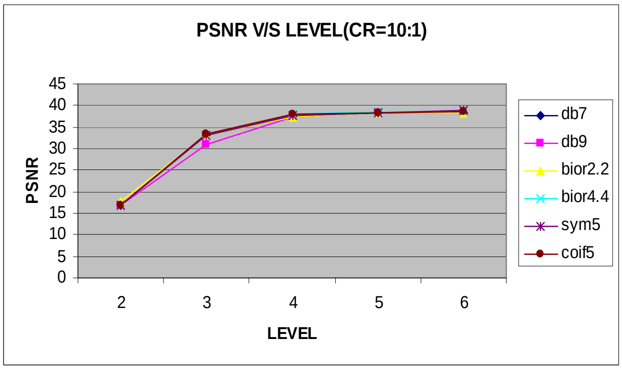

Fig. 3 PSNR V/S BPP(L=3,FIXED)

The optimal number of decompositions depends on filter order. Table-2 and Table-3 show the PSNR values for different filter order for fixed CR (10:1)and L=3.The response curves shown in fig2 and fig.3.It can be seen that as the number of decompositions increases , PSNR is increased up to some number of decompositions. Beyond that, increasing the number of decompositions has a negative effect. For L=5, Db7 gives 38.24db where as Db9 gives 38.16db.

5.5 . Computational Complexity

Computational complexity of the wavelet transform for an image size of Nx N employing dyadic decomposition is approximately [3]

$$C = 16.\ N^{2}\ .\ L\ (1 - 4^{-J})\ /\ 3 \qquad (4)$$

Where J and L are filter length and number of decompositions respectively. Computational complexity is represented as million of operations (MOP). Table-4 and fig.4 gives the MOP for different wavelet functions.

Table-4 Effect of filter order(J) and level of decomposition (L) on MOP.(CR=10:1)

WFL	Db7	Db9	Bior2.2	Bior44	Sym5	Coif5
2	2.795	2.795	2.621	2.785	2.793	2.793
3	4.193	4.193	3.932	4.177	4.190	4.190
4	5.591	5.591	5.242	5.570	5.586	5.586
5	6.989	6.989	6.553	6.962	6.983	6.983
6	8.387	8.387	7.864	8.355	8.380	8.380

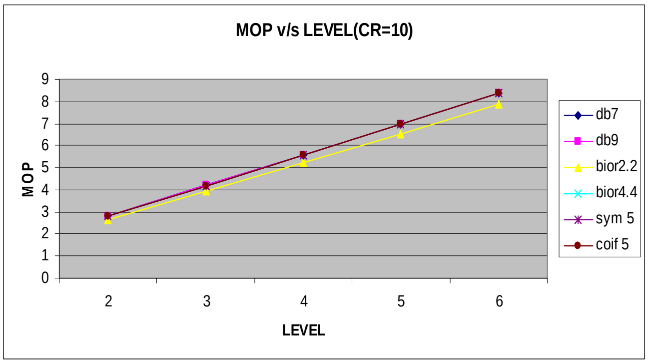

Fig.4 MOP V/S LEVEL OF DECOMPOSITION (CR=10,FIXED)

6. DWT Compression Results

The choice of optimal wavelet function in an image compression system for different image types can be provided. We used Lena test image for our simulation .The behavior of different wavelet functions and their characteristics have been studied .For each filter order in each family , the optimal number of decompositions can be found. The optimal number of decompositions gives the highest PSNR values in the wide range of compression ratios for a given filter order .

Table -4 show the optimal number of decomposition for a given bpp for different wavelet functions. Table 5, 6, 7, 8,9and10 give variation of PSNR with respect to bpp for different wavelet functions db7,db9, bior2.2 bior4.4 , sym5 and coif5 respectively. Fig.5,6,7,8,9,and10 show the response curves corresponds to PSNR V/S BPP for different wavelet functions db7,db9, bior2.2 bior4.4 , sym5 and coif5 respectively.

Performance Analysis (PSNR db), Test image Lena 512x512, 8bpp

Table-5 Variation of PSNR v/s BPP for Db7

L bpp	2	3	4	5	6
0.2	11.19	21.39	27.15	31.15	31.61
0.4	11.19	24.79	33.00	34.78	35.00
0.6	16.91	29.48	35.77	36.92	37.07
0.8	16.91	33.10	37.46	38.99	38.35
1.0	21.79	35.66	38.81	39.57	39.69
2.0	30.56	41.54	43.54	44.06	44.15

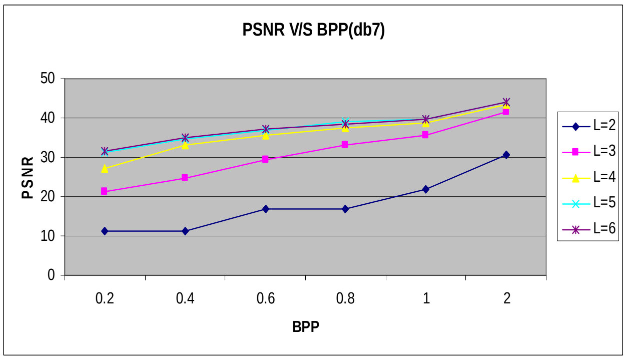

Fig. 5 PSNR V/S BPP(DB7)

Table-6 Variation of PSNR v/s BPP for Db9

L bpp	2	3	4	5	6
0.2	11.20	16.93	27.04	31.08	31.51
0.4	11.20	21.27	32.87	34.61	34.84
0.6	16.91	26.96	35.61	36.81	36.08
0.8	16.92	31.00	37.38	38.16	37.67
1.0	21.77	34.03	38.70	39.51	39.62
2.0	30.50	40.97	43.52	44.04	44.12

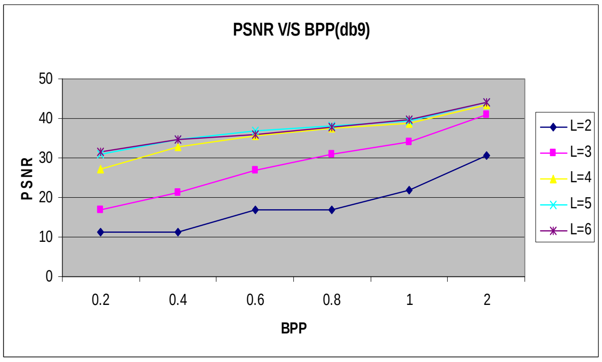

Fig. 6 PSNR V/S BPP(DB9)

Table-7 Variation of PSNR v/s BPP for Bior2.2

L bpp	2	3	4	5	6
0.2	12.03	17.70	28.48	31.04	31.39
0.4	12.03	25.95	33.23	34.44	34.79
0.6	17.87	30.19	35.89	36.65	36.74
0.8	17.88	33.15	37.38	38.13	38.22
1.0	23.01	35.66	38.65	39.14	39.21
2.0	31.31	41.39	43.17	43.50	43.56

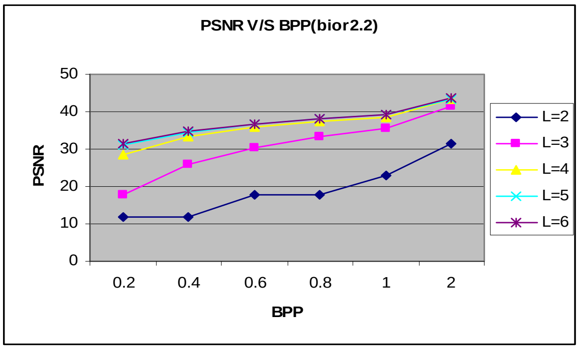

Fig.7 PSNR V/S BPP(bior2.2)

Table.8 Variation of PSNR v/s BPP for Bior4.4

L bpp	2	3	4	5	6
0.2	11.01	16.25	28.41	31.56	32.06
0.4	11.01	24.58	33.62	35.08	35.39
0.6	16.73	29.54	36.34	37.16	37.33
0.8	16.73	33.21	37.88	38.48	38.65
1.0	21.55	35.78	39.19	39.75	39.83
2.0	31.31	41.39	43.17	43.50	43.56

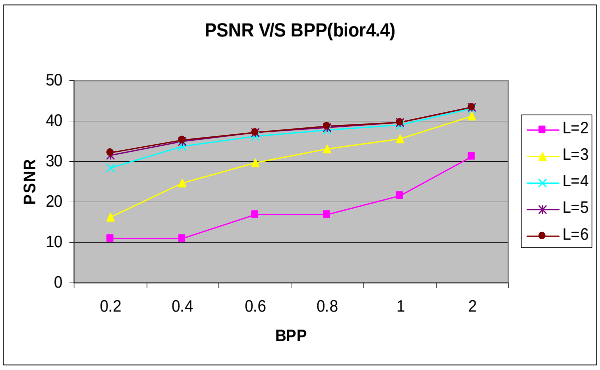

Table-9 **Variation of PSNR v/s BPP for Sym5**

L bpp	2	3	4	5	6
0.2	11.24	16.59	28.38	31.41	31.88
0.4	11.24	24.82	33.53	34.87	35.08
0.6	16.92	29.71	36.14	36.98	37.14
0.8	16.92	33.15	37.70	38.28	39.14
1.0	21.82	35.68	39.04	39.60	44.18
2.0	30.58	41.54	43.68	44.09	44.18

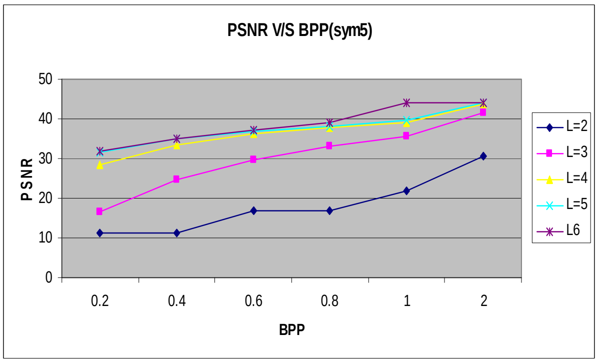

Fig. 9 PSNR V/S BPP(sym5)

Table-10 Variation of PSNR v/s BPP for Coif5

L bpp	2	3	4	5	6
0.2	11.20	16.58	28.33	31.41	31.88
0.4	11.20	24.88	33.68	34.99	35.20
0.6	16.92	29.73	36.31	37.13	37.27
0.8	16.93	33.32	37.82	38.37	38.52
1.0	21.79	35.83	39.15	39.72	39.82
2.0	30.68	41.64	43.76	44.17	44.26

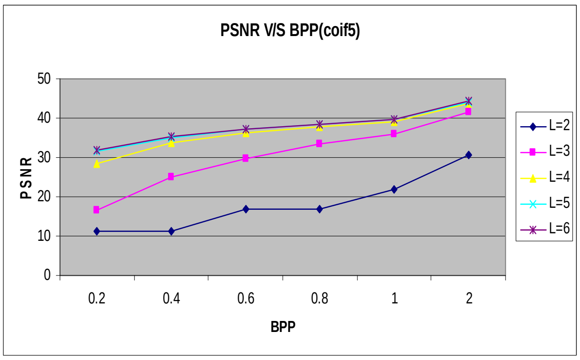

Fig.10 PSNR V/S BPP(coif5)

7. Conclusions

Wavelet analysis is very powerful and extremely useful for compressing data such as images. Its power comes from its multiresolution. The performance of SPIHT compression algorithm is done in Mat lab for different types of wavelets. The results proved to be more useful in understanding the effects of decomposition levels, filter order and different wavelet functions.For a given image, it is possible to select a wavelet function, decomposition level and bpp to match a required PSNR. The results suggests that no particular wavelet function is ideal for a given image and bit rate (CR). Even order of the filter (J) and level of decomposition (L) is also a trade-off parameter for a given input. But it can be concluded that L=3 is minimum to meet required PSNR and L> 4 no much improvement in PSNR and MOP increases.

The decomposition level changes the proportion of detail coefficients in the decomposition. Decomposing a signal to a greater level provides extra detail that can be thresholded in order to obtain higher compression rates. However this also leads to energy loses. The best trade-off. between energy loss and compression is provided by decomposing to levels 3 and 4. Decomposing to fewer levels means provides better energy retention but not as great compression, decomposing to higher levels provides better compression but more energy loss.

The type of wavelet affects the actual values of the coefficients and hence how many detail coefficients are zero or close to zero and therefore how much energy and zeros can be obtained. Wavelets that work well with an image redistribute as much energy as possible into the approximation sub signal, while giving a large proportion of the coefficient value to describe details

Wavelet Bior2.2 gives optimum results at L=3 with lowest possible MOP.

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[11] Coding of Still Pictures ISO/IEC JTC1/SC29/WG1 (ITU-T SG8)

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