Color image compression technique for pattern recognition using Block Truncation Coding, Discrete Wavelet Transform, Embedded zerotree transform and fractal image compression

Yalavarthi Ramakrishna[1], V.Purna Chandra Rao [2]
[1] Research scholar,Rayalaseema university, Kurnool, Andhra Pradesh, India.
[2] Professor, Holy Mary Institute Of Technology And Science Hyderabad, India.

Abstract – In this paper we analyze the performance difference of different color image compression techniques for pattern recognition i.e. block truncation coding (BTC), wavelet, embedded zerotree transform and fractal image compression. This paper focuses important features of transform coding in compression of still images, including the extent to which the quality of image is degraded by the process of compression and decompression. The above techniques have been successfully used in many applications. The techniques are compared by using the performance parameters PSNR, CR and reduced size. Images obtained with those techniques yield very good results. Out of these techniques BTC and wavelet are symmetrical compression techniques, EZW and fractal are asymmetrical compression techniques. Symmetrical compression means encode time and decode time are same and almost negligible while in asymmetrical encode and decode time is different and it lake lot of seconds to compress the image.

Index Terms – Image Compression, Pattern Recognition, BTC, PSNR, CR, EZW.

1. INTRODUCTION

1.1. Image

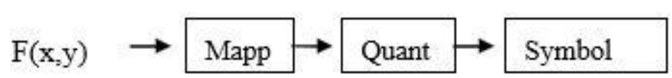
An image is essentially a 2-d signal processed by the human visual system. The signals representing images are usually in analog form. However, for processing, storage and transmission by computer applications, they are converted from analog to digital form. A digital image is basically a 2-dimensional array of pixels. Images form the significant part of data, particularly in remote sensing, biomedical and video conferencing applications. The use of and dependence on information and computers continue to grow, so too does our need for efficient ways of storing and transmitting large amounts of data [1].

1.2 Image Compression

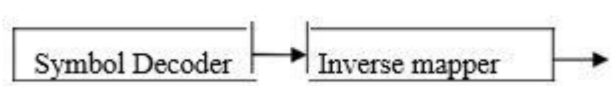
Image compression addresses the problem of reducing the amount of data required to represent a digital image. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. Compression is achieved by the removal of one or more of the three basic data redundancies:

i. Coding redundancy
ii. Interpixel redundancy
iii. Psycho visual redundancy

Coding redundancy is present when less than optimal code words are used. Interpixel redundancy results from correlations between the pixels of an image. Psycho visual redundancy is due to data that is ignored by the human visual system (i.e. visually non-essential information). Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. An inverse process called decompression (decoding) is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible. Image compression systems are composed of two distinct structural blocks: an encoder and a decoder [2].



Compressed image



Uncompressed Image

Image f(x,y) is fed into the encoder, which creates a set of symbols form the input data and uses them to represent the image. If we let n1 and n2 denote the number of information carrying units(usually bits) in the original and encoded images respectively, the compression that is achieved can be quantified numerically via the compression ratio, CR = n1 /n2 (1)

As shown in the figure, the encoder is responsible for reducing the coding, interpixel and psycho visual redundancies of input image. In first stage, the mapper transforms the input image into a format designed to reduce interpixel redundancies. The second stage, quantizer block reduces the accuracy of mapper's output in accordance with a predefined criterion. In third and final stage, a symbol decoder creates a code for quantizer output and maps the output in accordance with the code. These blocks perform, in reverse order, the inverse operations of the encoder's symbol coder and mapper block. As quantization is irreversible, an inverse quantization is not included [3].

2. BLOCK TRUNCATION CODING

Block truncation coding (BTC) was first developed in 1979 for grayscale image coding. This method first divides the image to be coded into small non overlapping image blocks (typically of size 4*4 pixels to achieve reasonable quality). The small blocks are coded one at a time. For each block, the original pixels within the block are coded using a binary bit-map the same size as the original block and two mean pixel values. The method first computes the mean pixel value of the whole block and then each pixel in that block is compared to the block mean. If a pixel is greater than or equal to the block mean, the corresponding pixel position of the bitmap will have a value of 1, otherwise it will have a value of 0. Two mean pixel values, one for the pixels greater than or equal to the block mean and the other for the pixels smaller than the block mean are also calculated. At decoding stage, the small blocks are decoded one at a time. For each block, the pixel positions where the corresponding bitmap has a value of 1 is replaced by one mean pixel value and those pixel positions where the corresponding bitmap has a value of 0 is replaced by another mean pixel value[19]. It was quite nature to extend BTC to multi spectrum images such as color images and a number of authors have suggested various methods .The simplest extension was to view a color image as consisting of three independent grayscale images and apply BTC to each color plane independently. The disadvantage of this method is that three bit planes are needed hence the compression ratios achievable are low. A more aggressive approach is to exploit the redundancy exits between spectrum bands by using only a single bit map for all the spectral bands. In this work, we used single bit plane BTC. Most color images are recorded in RGB space, which is perhaps the most well-known color space. Various other color spaces that are suited for different image processing tasks also exist. Through psycho visual experiment, we found that the visual quality of the BTC coded images was not greatly affected by color quantizing the mean colors. Therefore, for each BTC coded image, a color table (palette) consists of 256 colors are constructed and stored. The mean colors are coded (8 bits per mean color) as the indices of the colors in the color table that are the closest to the mean colors. Therefore the bit rate in our scheme is 2 bits/pixel or 12: 1 compression, plus 768 bytes (256 3 bytes) color table overhead in each image. Our content descriptors are derived from such a BTC coded scheme. In this technique first empty matrix of same Size of image matrix is created for reconstructing image[5].

Then compression is applied on red plane by calculating first number of non overlapping blocks required to cover the entire input image by equation:

nbx=size (dvalue, 1)/bx; *(2)*

nby=size (dvalue, 2)/by; *(3)*

Where bx, by are x block size, y block size of compression matrix.

nbx, nby is number of non overlapping blocks, dvalue is reconstructed matrix

Then matrix of bx * by is created in which value of current pixel is stored and average color level of the current block is calculated by:

m=mean (mean (blocco)); *(4)*

Where blocco is current block

The compressed data which correspond to the input image is stored in red plane and then green plane and blue plane created in same way.

3. WAVELET

Wavelets are having an average value of zero and it can be defined over a finite interval. The process behind the wavelet transform is any arbitrary function (t) can be defined in the form of a superposition of a set of such wavelets or basis functions. These basis functions are simply called as the baby wavelets. These baby wavelets are obtained from the mother wavelets by scaling (contractions) and shifts (translations). The Discrete Wavelet Transform of a finite length signal is represented as x(n). It is having N components and it can be represented by an N x N matrix. The Wavelet based transform can also be called as Sub band coding. Because there is no need to block the input image and its basis functions, have variable length. The blocking artifacts can be avoided if the wavelet based schemes performed in a higher compression ratio[6].

The wavelet uses subband coding to selectively extract different subbands from the given image. These subbands can then be quantized with different quantizers to give better compression. The wavelet filters are specifically designed to satisfy certain constraints called the smoothness constraints. The wavelet filters are designed so that the coefficients in each subband are almost uncorrelated from the coefficients in other subbands. The wavelet transform achieves better energy compaction than the DCT and hence can help in providing better compression for the same Peak Signal to Noise Ratio (PSNR).

In this first noise is inserted to the image.

IMNOISE (I,'speckle', V) (5)

It adds multiplicative noise to the image I, using the equation J = I + n*I, where n is uniformly distributed random noise with mean 0 and variance V. Then decomposition matrix is created by equation

[C, S] = WAVEDEC2(X, N,'wname') (6)

Returns the wavelet decomposition of the matrix X at level N, using the wavelet named in string 'wname'. Outputs are the decomposition vector C and the corresponding bookkeeping matrix S. N must be a strictly positive integer. Then threshold of wavelet coefficients calculated by:

[THR,NKEEP] = WDCBM2(C,S,ALPHA,M) (7)

Returns level-dependent thresholds THR and numbers of coefficients to be kept NKEEP, for de-noising or compression. THR is obtained using a wavelet coefficients selection rule based on Birge-Massart strategy. Then compressed image is obtained by wavelet packet coefficients thresholding by equation

[compressed_image,TREED,comp_ratio,PERFL2]=WPDENCMP(thr,'s', n,'haar','threshold', 5, 1);

(8)

Where 'thr' (2-D) obtained by wavelet packet coefficients thresholding. The additional output argument TREED is the wavelet packet best tree decomposition of compressed_image. PERFL2 and PERF0 are L^2 recovery and compression scores in percentages. Multi-level 2-D wavelet reconstruction.

4. EMBEDDED CODING

In embedded coding, the coded bits are ordered in accordance with their importance and all lower rate codes are provided at the beginning of the bitstream. Using an embedded code, the encoder can terminate the encoding process at any stage, so as to exactly satisfy the target bit-rate specified by the channel. To achieve this, the encoder can maintain a bit count and truncate the bit-stream, whenever the target bit rate is achieved. Although the embedded coding used in EZW is more general and sophisticated than the simple bit-plane coding, in spirit, it can be compared with the latter, where the encoding commences with the most significant bit plane and progressively continues with the next most significant bit-plane and so on. If target bit-rate is achieved before the less significant bit planes are added to the bit-stream, there will be reconstruction error at the receiver, but the "significance ordering" of the embedded bit stream helps in reducing the reconstruction error at the given target bit rate[12].

Relationship between subbands

In a hierarchical subband system, which we have already discussed in the previous lessons, every coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. Only, the highest frequency subbands are exceptions, since there is no existence of finer scale beyond these. The coefficient at the coarser scale is called the parent and the coefficients at the next finer scale in similar orientation and same spatial location are the children. For a given parent, the set of all coefficients at all finer scales in similar orientation and spatial locations are called descendants. Similarly, for a given child, the set of coefficients at all coarser scales of similar orientation and same spatial location are called ancestors [13].

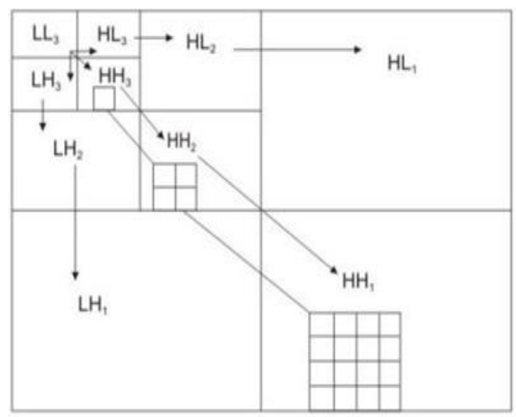


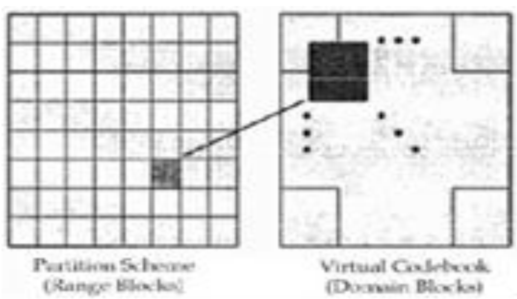
Fig.1 illustrates this concept, showing the descendants of a DWT coefficient existing in HH3 subband. Note that the coefficient under consideration has four children in HH2 subband, since HH2 subband has four times resolution as that of HH3. Likewise, the coefficient under consideration in HH3 subband has sixteen descendants in subband HH1, which in this case is a highest-resolution subband. For a coefficient in the LL subband, that exists only at the coarsest scale (in this case, the LL3), the hierarchical concept is slightly different. There, a coefficient in LL3 has three children – one in HL3, one in LH3 and one in HH3, all at the same spatial location. Thus, every coefficient at any subband other than LL3 must have its ultimate ancestor residing in the LL3 subband.

5. FRACTAL IMAGE COMPRESSION

Fractal is one effective method to describe natural modality in the process of transformation and iteration. In 1973, Benoit Mandelbrot firstly brought forward the idea of fractal geometry, Infinity self-similarity is the soul of fractal. It was Michael Barnsley and his research group who first give out the method of fractal-based image compression, via IFS (Iterated Function Systems), according to the local and global selfsimilar principle. In 1989, Amaud Jacquin and Michal Barnsley realized a first automatic fractal encoding system [14].

Fractal image compression is also called as fractal image encoding because compressed images are represented by contractive transforms. These transforms are composed of collection of a number of affine mappings on the entire image, known as Iterated Function System (IFS). Contractive transformation is applied to the IFS's called Collage theorem. This theorem is the technique core of the fractal coding. Fractal image compression is a modern image compression technique based on self-similarity.

In FIC the image is decomposed twice, into overlapping domain blocks with size D*D to make a domain pool. Then we decompose the image again into non-overlapping range blocks with size R*R, and usually D=2*R. This type of decomposition is closely related to quad –tree (parent child relationship) where domain block forms parent and small four range block forms children. The whole process of fractal image encoding is shown in Fig. 2.



After decomposition, for each range block we search for best matched domain block in the domain pool with a contractive affine transformation Where *x* and *y* are the spatial coordinates of the image block and *p*xy is the pixel value at the position (*x*,*y*); *a*i, *b*i, *c*i and *d*i denote the combinations of some of the eight symmetrical transformations; *u*i, *v*i are the location luminance values; *s*i is the scaling coefficient; *o*i is the luminance offset. With the definition of equation (1), the matching search between the range blocks and the extended domain blocks is carried out by solving the minimizing problem as follows.

$$E(R,\hat{D}) = \min\left\|R - (s \cdot \hat{D} + o \cdot I)\right\|$$

Finally, with the equation (1) and (2), the best matched domain block can be found for each range block in the original image.

6. EXPERIMENTAL RESULTS

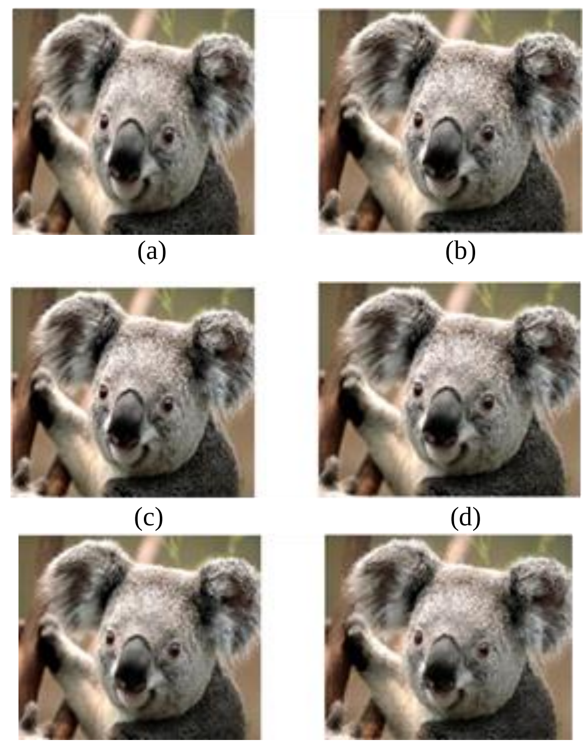
The four schemes discussed and elaborated here are simulated on MATLAB platform. The compression efficiency is measured using the CR. The quality of the image is analyzed by measuring PSNR and MSE. Koala.jpg image is taken for experiment whose original size is 780831 bytes.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2 \quad (11)$$

$$PSNR = 10\log_{10}\frac{MAX^2}{MSE} = 20\log_{10}\frac{MAX_I}{\sqrt{MSE}} \quad (12)$$

6.1 Results of BTC Image Compression Technique

The Block Truncation Coding (BTC) image compression technique is applied to koala.jpg image with varying block values. BTC computation on jellyfish image gives maximum PSNR of 34.3960 at block=2*2. Fig. 3 gives information about the computation of BTC algorithm by varying rank of block size.



(a) (b) (c) (d) (e) (f)

Figure 3 Computation of BTC algorithm by (a) original image (b) block= 2*2, (c) block=4*4, (d) block=8*8 , (e) block=16*16 and (f) block =32*32

TABLE I PERFORMANCE EVALUATION OF BTC ALGORITHM

Block	PSNR	Compressed Size	CR
2*2	34.3960	142232	5.489

4*4	30.5924	140862	5.543
8*8	27.8783	143515	5.440
16*16	25.7429	147767	5.284
32* 32	23.4524	146256	5.338

6.2 Results of Wavelet Image Compression Technique

The wavelet technique is applied to same koala image with different decomposition level. In wavelet algorithm with increase in decomposition level size start increases. The PSNR value tends to remain same at every decomposition level. Fig. 4 gives information about the computation of BCT algorithm by varying block size. Table-II represents performance summary and investigation of wavelet algorithm.


(a)


(b)


(c)


(d)


(e)

Figure 4 Computation of wavelet algorithm by (a) at decomposition level 1, (b) at decomposition level 2, (c) at decomposition level 3, (d) at decomposition level 4, (e) at decomposition level 5.

TABLE II PERFORMANCE EVALUATION OF WAVELET ALGORITHM

Level	Size compressed	Psnr	Cr ratio
1	186852	28.5050	4.178
2	187011	28.5146	4.175
3	186846	28.5443	4.179
4	186896	28.5079	4.177
5	187000	28.5005	4.175

6.3 Results of EZW Image Compression Technique

The EZW is asymmetrical techniques means encode time i.e. compression time and decode time i.e. decompression time are different. In EZW decode time is large as compared to encode time. Results are calculated on same image koala.jpg.


(a)


(b)


(c)


(d)


(e)

Figure 5 Computation of EZW algorithm by (a) at decomposition level 1, (b) at decomposition level 2, (c) at decomposition level 3, (d) at decomposition level 4, (e) at decomposition level 5.

TABLE II PERFORMANCE EVALUATION OF EZW ALGORITHM

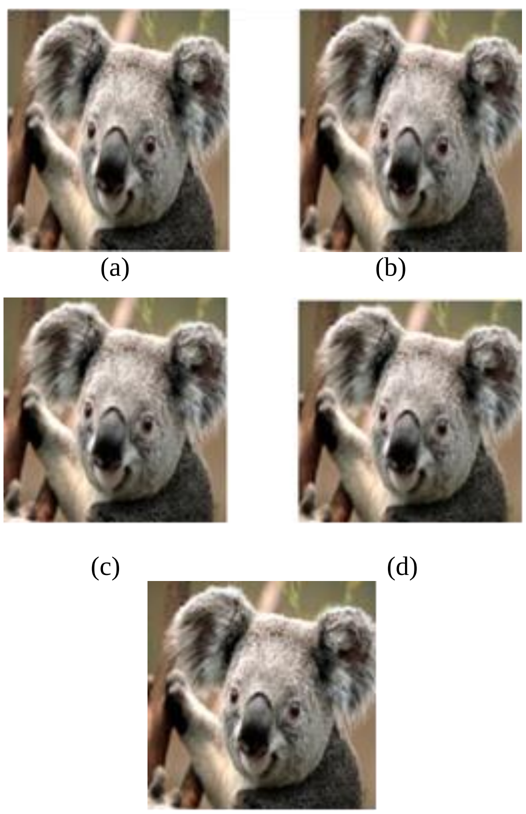
level	PSNR	Compressed Size	encode	Decode	CR
1	32.74	14534	570.7030	1.6598e+003	53.724
2	31.61	11676	228.6430	579.2290	66.874

3	31.05	11073	135.3750	344.4880	70.516
4	30.93	11119	131.0300	317.3060	70.224
5	30.94	11132	117.4800	374.2750	70.142

The PSNR value is maximum at decomposition level 1. Fig. 5 gives information about the computation of EZW algorithm by varying decomposition level. Table-III represents performance summary and investigation of EZW algorithm. Encode time is maximum at decomposition level 1 and then decrease with increase of decomposition level.

6.4 Results of Fractal Image Compression Technique

The Fractal image compression is also asymmetrical techniques means encode time and decode time are different. In FIC encode time is large as compared to decode time. Results are calculated on same image koala.jpg. Decode time is almost negligible as compare to encode time.



(a) (b) (c) (d) (e)

Figure 6: Computation of FIC algorithm by (a) at Increase in Size of block by 1 unit, (b) at Increase in Size of block by 2 unit, (c) at Increase in Size of block by 3 unit, (d) at Increase in Size of block by 4 unit, (e) at Increase in Size of block by 5 unit.

Increase in Size of block	PSNR	Compressed Size	encode	decode	CR
1	24.5889	45088	544.7890	50.5500	17.3179
2	24.0234	43310	701.0580	49.3030	18.0289
3	23.9575	43460	805.7400	49.0130	17.9667
4	23.8018	43122	702.2690	49.7390	18.1075
5	23.8944	42918	871.7400	49.3430	18.1936

The PSNR value is maximum when search block size is increases by 1 unit. Fig. 6 gives information about the computation of FIC algorithm by varying search block size. Table-IV represents performance summary and investigation of FIC algorithm. Encode time is vary with size of search block.

7. CONCLUSION

Four image compression techniques i.e. Block truncation coding (BTC), wavelet, embedded Zerotree wavelet transform and fractal image compression (FIC) are compared. The results reveal that images can be compressed as application demands, but redundant information is added as more coefficients are added and simultaneously time taken to compress the image and data storage needed increases. Using BTC computation, an image matrix can be compressed to a significantly smaller sized matrix, and during decomposition, the image portray almost an identical to original image. This in turn saves a lot of memory space. In this the original block truncation coding (BTC) based on dividing the image into non-overlapping blocks and uses a two-level quantization. Here the average value of block considered for compressed (i.e. for finding mean and standard deviation) is 2*2 and gives optimal image quality as depicted. The significant advantage of wavelet is that it store values of time domain and frequency domain, which is an efficient method to eliminate redundant data and provides flexibility. It uses wavelet decomposition level with most energy. In EZW encode time is small as compared to decode time. The coded bits are ordered in accordance with their importance and all lower rate codes are provided at the beginning of the bit stream. in FIC blocks are compared domain block and range block which are then stored in code book for reconstruction process. Encoding time and decoding time of FIC is less as compared to EZW. It provides better PSNR when size of search block is increased by one unit 1 as depicted. A comparison between the image resolutions reveals that the output images obtained from projected work resemble the original images. Consequently, EZW algorithm gives good result and but it take lot of time for compression but BTC provide better result subjectively (good visual quality) and objectively (MSE, PSNR) as compared to other techniques. Mathematically compression ratio of EZW is much better as compared to all other techniques, so it is better one for compressing an image to large degree.

REFERENCES

[1] Rafael c. Gonzalez, richard eugene; "digital image processing", edition 3, 2008.
[2] Ismail avcibas, nasir memon, bulent sankur, khalid sayood, " a progressive lossless / near lossless image compression algorithm,"IEEE signal processing letters, vol. 9, no. 10, pp 312-314, october 2002.
[3] Ming yang & nikolaos bourbakis ,"an overview of lossless digital image compression techniques," circuits & systems, 2005 48th midwest symposium ,vol. 2 IEEE ,pp 1099-1102,7 – 10 aug, 2005.
[4] Hong zhang, xiaofei zhang & shun cao, " analysis & evaluation of some image compression techniques," high performance computing in asiapacific region, 2000 proceedings, 4th int. Conference, vol. 2, pp 799-803,14-17 may, 2000.
[5] Guoping qiu, "color image indexing using btc", IEEE transactions on image processing, vol. 12, no. 1, january 2003.
[6] S. A. Abdul, k. B. A. Karim," wavelet transform and fast fourier transform for signal compression: a comparative study", 2011 international conference on electronic devices, systems and applications 2011 IEEE.
[7] S.p.raja, n.n. Prasanth , s.a. Abdul rahuman, s.k. Jinna, s.p.princess "wavelet based image compression: a comparative study" international conference on advances in computing, control, and telecommunication technologies 2009 IEEE pp: 545 - 549 , dec. 2009.
[8] P. Aggarwal & b. Rani, "performance comparison of image compression using wavelets" international journal of computer science & communication vol. 1, no. 2, pp. 97-100, july-december 2010.
[9] Patricia r. Oliveira, roseli f. Romero, luis g. Nonato, "techniques for image compression: a comparative analysis", pp:249-254 2000 IEEE.
[10] J. Shukla , m. Alwani, a. K. Tiwari, "a survey on lossless image compression methods" 2nd international conference on computer engineering and technology, vol 6, pp:136-141, 2010 IEEE.
[11] C. Christopoulos, a. Skodras and touradj ebrahimi, "the jpeg2000 still image coding system: an overview," IEEE transactions on consumer electronics, vol. 46, no. 4, nov. 2000, pp. 1103-1127.
[12] Chong fu , zhi-liang zhu "a dct-based fractal image compression method" international workshop on chaos-fractals theories and applications, pp:439-443, 2009 IEEE.
[13] Shih-tu hsiang and john w woods "embedded image coding using zeroblocks of subbandnavelet coefficients and context modeling", IEEE international symposium on circuits and systems, pp:662-665, 2000.
[14] R. R. Shively, e. Ammicht, p. D. Davis "generalizing spiht: a family of efficient image compression algorithms" pp: 2059- 2059, 2000 IEEE.
[15] E. Zhao, d. Liu," fractal image compression methods: a review" proceedings of the third international conference on information technology and applications 2005 IEEE.
[16] B. Wohlberg and g. D. Jager "a review of the fractal image coding literature" IEEE transactions on image processing, vol. 8, pp; 1716-1729, december 1999.
[17] G. W. Hui "image compression algorithm based on fractal-wavelet" international workshop on chaos-fractals theories and applications ,pp;430-434, 2009 IEEE.
[18] Lin hu, qi-an chen and danqing zhang "an image compression method based on fractal theory " the 8th international conference on computer supported cooperative work in design proceedings, pp:546-550, 2003 IEEE.
[19] Doaa Mohammed, Fatma Abou-Chadi, "Image Compression Using Block Truncating Code", JSAT, pp 9 – 1, 2011.