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Design of an Efficient Wavelet-Based Image Compression Model for Digital Images: A Review

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Abstract: *Image compression is a technique which removes the extraneous or unrelated information. For compression and decompression, a number oftechniques such as Shannon Fano Technique,Lempel Ziv Welch, Run length Coding technique, Huffman technique etc. have been applied. In this paper, the different lossless image compression techniques have been studied. Further, a Comparative study on various techniques has been carried out and found that Embedded Zerotree Wavelet (EZW) and Set Partition in Hierarchical Transform (SPIHT)techniques perform better in terms of Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Mean Square Error(MSE).*

Keywords: Image compression, Lempel-Ziv Welch encoding, Run Length encoding, Huffman encoding, Shannon-Fano encoding, Embedded zerotree wavelet (EZW), Set partitioning in hierarchical transform (SPIHT)

I. INTRODUCTION

Digital image may be lossless or lossy depending upon the quality of images. For medical image, comics and technical drawing, lossless image compression is used. These methods are used specially for high bit rate transfer of an image. The most common quality of a digital image is that neighborhood pixels are convoluted to the main pixels. Hence, neighborhood pixels have redundant information [1]. Image compression has two components, one is redundancy and another one is Irrelevancy. The duplication of an image is removed by the redundant component. A signal is produced by human visual system by the use of irrelevancy component. Since the limitation of bandwidth and high speed data transfer image compression technique is used. There are two process involve during the transmission of data. One is data encoding and another one data decoding. Encoding, known as compression involve reduction of bits from the original message or image. It means reduce the size of data due to band limitation of channel. In the receiver end, reverse process occur. That process is known as decompression or decoding. It means to recover the uncompressed data from the compressed data. The lossless compression is also known as reversible compression, because in lossless compression technique we get the final output exactly same as the input [1].

Figure 1 shows the steps for Image compression and decompression.

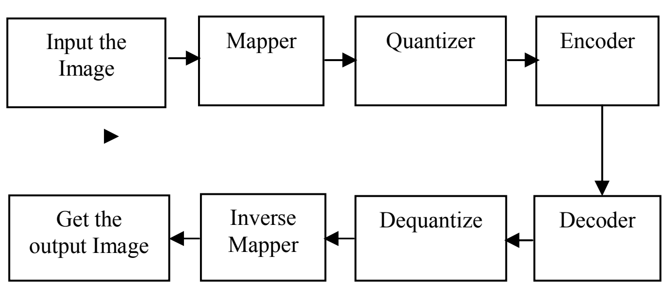

Figure 1: Steps of Image Compression and Decompression [2]

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As shown in Figure 1, first of all input image is taken from the data set. Then image is fed to the Mapper. Mapper convert the input image into inter pixel coefficients. Quantizer reduced these inter pixel coefficients into small values or we can say Quantizer convert large values into small values so it results some kind of data loss. Entropy encoder compressed these Quantized values and improves the compression. The decoder, Dequantizer and inverse Mapper obtained here to reconstruct the image and this process is called Decompression. The image can be reconstructed without any loss in the image. The main problem of lossless image compression is peak signal to noise ratio. There is degradation of peak signal to noise ratio. EZW and SPIHT techniques are best algorithm for such type of problem [2].
The overall past work is describe in Section II. Section III describes the different Lossless techniques. Comparison of some compression techniques has been given in section IV. Result describe in section V. Finally, Section VI describes the conclusion of paper.

II. LITERATURE REVIEW

Many researchers have adopted different methods for lossless image compression and described in following section.
K. Cabeen, ***et. al*** in 1998 proposed image compression and discrete cosine transformation. The PSNR was achieved for different values of bits. The PSNR value for 0.125, 0.25, 0.5 and 1 was 29.23, 31.45, 34.23 and 39.13 respectively [3].
J. G. Apostolopoulos, ***et. al.*** in 1999 offered the context based adaptive lossless video compression standard coding for compression. BPP of video was improved with this technique. It was improved up to 5.8957 [4].
T. *D, et. al.* in 2000 proposed embedded block coding with optimized truncation of embedded bit stream method. The PSNR was achieved for different values of bits . The PSNR value for 0.125, 0.25, 0.5 and 1 was 31.10, 34.11, 37.21 and 40.41 respectively [5].
M. J. Weinberger, ***et. al.*** in 2000 offered low complexity lossless compression technique. The average bit rate was 3.51. Performance was improved up to 2.5 % [6].
X. Li, ***et. al.*** in 2001 proposed a most efficient LS based adaption method . In this paper, BPP has been taken as performance parameter in different order of images . For the 1storder , it was improved up to 5.02 and for the 2nd order it was improved up to 4.5 [7].
E. Syahrul ***et. al.*** in 2008 proposed improved Burrows Wheeler Transform (BWT). In this average compression ratio is calculated for different bits. The compression ratio for 1 bit, 2 bit, 4 bit, 8 bit was 2172, 2229,2189 and 2231 respectively [8] .
Kavitha, ***et. al.*** in 2008 proposed a most efficient arithmetic coding . In this paper, pixel ratio is performance parameter in different order of images. The pixel ratio was improved up to 5.089 [9].
Gorley, ***et. al. i***n 2008 demonstrated stereoscopic image quality and metric compression. It was based on image enhancement and compression. In this work, Bit Rate and signal to noise ratio was achieved up to 4.059 and 71.59 [10].
J. Kim, ***et. al.*** in 2009 proposed a significant truncation coding in which reduction ratio and throughput is improved. Reduction Ratio and throughput was achieved up to 60.4 and 14.2 [11].
K. H. Talukder, ***et. al.*** in 2010 offered HARR wavelet approach. In this paper, The average bit rate was 4.41. Performance was improved 3.8 % that of CALIC [12].
Mozammil, ***et. al.*** in 2012 proposed a most efficient MS based descriptive method . This method is used for videos. In this work, BPP is performance parameter in different order of videos. For the 1st order, it was improved up to 7.14 and for the 2nd order it was improved up to 6.45 [13].
A. Shahbahrami, ***et. al.*** in 2012 proposed the methodology based on arithmetic coding. In respect to survey, MSE, PSNR and CR were the performance parameter. MSE, PSNR and CR were achieved up to 89.43, 25.43 and 6.58 respectively [14].
Horng, ***et. al.*** in 2012 described vector quantization algorithm using firefly approach. Bit rate was achieved up to 4.8958 db [15] .
D. Kaur, ***et. al.*** in 2013 gives the overview of different lossless compression techniques such as Huffman coding, Shannon Fano coding, LZW, RLE etc. [16].

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Ma, Kede, ***et. al.*** in 2015 proposed an algorithm to compress high dynamic range to low dynamic range. In this work, toned image quality index is performed to search out the compressed image. The average value was improved up to 0.60 [17].

S. R. Kodituwakku, ***et. al. i***n 2015 demonstrated improved lossless technique for text data. It was based on texo-algo. For the delta values, Bit Rate and signal to noise ratio was achieved up to 4.08 and 50.44 [18].

Rinaldi, Pierluigi, ***et. al.*** in 2016 proposed the methodology for different medical images. In respect to survey, MSE, PSNR and CR were taken as the performance parameter. MSE, PSNR and CR were achieved up to 95.57, 28.33 and 7.783 respectively [19].

Ding, J. Jiun, ***et. al.*** in 2016 offered the context based adaptive lossless image coding for compression. Bit per pixel (BPP) has been improved with this technique. It was improved up to 4.9649 [20].

M. A. Rahman, ***et. al.*** in 2016 utilized powerful diffusion methods. BPP, PSNR and entropy were the performance parameter. These were improved up to 0.344, 16.83 and 7.83 [21].

D. Chen, ***et. al.*** in 2017 described invertible update-then-predict integer lifting wavelets approach. Bit rate was achieved upto 5.808060 [22].

J. G. Sobrino, ***et. al. i***n 2017 demonstrated improved lossless technique. It was based on predicting temperature and dew point temperature. For the delta values , Bit Rate and signal to noise ratio was achieved up to 5.06 and 75.55. [23]

III. COMPRESSION TECHNIQUES

There are a number of compression techniques but in this paper we have study only lossless compression techniques.

A. Huffman coding
B. Shannon-Fano Coding
C. Run Length Coding (RLE)
D. Lempel -Ziv Welch (LZW)
E. Embedded Zerotree Wavelet (EZW)
F. Set Partition in Hierarchical Trees (SPIHT)

Huffman Encoding

Huffman coding is a lossless image compression technique. Huffman coding is used in the greedy choice property to reduce data without any loss of information. It is based on the frequencies that are based on the length of the assigned codes, so it is also known as greedy algorithm. It is Bottom-Up approach. It is based on the variable length code that is known as Prefix codes. The goal of the Huffman coding is to reduce the total no. of bits used without any loss of information. Huffman coding is an optimal pre-character coding method. Before compressing data input stream is analyze, represented data using variable length code. Codeword assigned to each letter and these codeword are produced by traversing the Huffman tree. One of the property of Huffman coding is that, no of codeword produced is the prefix of another. Letter that are appearing frequently have short codeword and Letter that appearing rarely have long codeword [3].

Shannon - Fano Coding

Shannon-Fano coding is also a type of lossless compression technique. It is a technique for constructing the prefix code that based on symbols and probability or in short we say that it is an algorithm used to compress the strength. It is a Top-Down approach. It is suboptimal but like Huffman coding it does not achieve lowest possible predictable codeword length. It is a simple code so it is not usually used because it is not efficient as Huffman coding. It is similar to Huffman coding but only differ in the way that it builds the binary tree of symbol nodes. In this coding, in the first step first group the symbol nodes into two sets of symbols having equal frequency counts and assign a single bit (0,1) for each subset. In the second step repeat step 1 for two newly generated sets until only one symbol left in each set [3-4]. After this the same encoding process that used in Huffman coding is employed for Shannon Fano coding. These

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techniques sometimes generate codes that are longer than the Huffman codes. During the study of many research paper it has been conclude that Huffman coding is better than Shannon fano coding in terms of CR, PSNR and MSE [3-4].

Run Length Coding (RLE)

Run length coding is also a lossless compression technique. It is a simple lossless algorithm based on the principle that when there is a sequence of repeated data value then by using RLE repeated sequence of data values is replaced with single value and count number [3-4] Run length coding algorithm is used on the repeated sequence of data values. For example if we have a repeated sequence of data values or we can say a string i.e. AAAAGGGRRRKKYTTTT, It is called a Run. When we used RLE on this string then here AAAA is four times, we write it as 4A, GGG is three times we write it as 3G, RRR is three times we write it as 3R, KK is two times we write it as 2K, Y is one time we write it as 1Y and TTTTT is four times we write it as 4T. By doing this we found that the length of the repeated string is 4A3G3R2K1Y3T. so we can say that Run Length Coding is a simple way to compress the size of data but it is not useful for larger data so it is not usually used because it is not efficient as Huffman and Shannon- Fano coding [3-4].

Lempel Ziv Welch (LZW)

Lempel Ziv Welch is also a type of lossless compression technique. LZW is a dictionary based coding and can be static or dynamic. In static, dictionary is fixed for both compression and decompression process but in dynamic, dictionary is not fixed for compression and decompression process. LZW map variable number of symbol to fixed length code. It is only used for English text and it contain too many bits and every bits need a dictionary that's why it is not usually used for compression [3-4].

EZW Algorithm

Embedded Zerotree Wavelet (EZW) is proposed by J. M. Shapiro. EZW is basically a improved version of discrete wavelet encoding. It is competently representing portion of the encoded symbol stream that can be safety eliminated. This could be done by aggregate energy below predetermined threshold [11, 23].

The EZW Algorithm has the following steps.

Step 1

In 1st step maximum value of the DWT coefficient in matrix is decided as initialized threshold. In EZW algorithm, maximum value of the initial is found out. We have to scan the entire wavelet coefficient matrix [9]. We found that most of the coefficient is highly significant in low frequency sub-band (LL band).In this for coding of an image, two passes are used. Ist pass is dominant, in this pass the image is scanned and for each coefficient a symbol is given [11].

Step 2

In this pass, a significant map and threshold value is compare with threshold value. The significance map can be used four symbols that can be represented as a string of symbol.

Zero tree root (t): It means if the absolute value have lower value than the particular threshold value. Then for the zero tree root , all the children have also lower value than its threshold value.

Isolated Zero (Z): if threshold value is greater than the absolute value but absolute value of its one child is higher than the threshold value called isolated zero.

Significant positive (p): if the absolute value is higher than threshold with a positive sign is called positive significant.

Significant negative (n): if the absolute value is lower than threshold with a negative sign is called negative significant.

Step 3 (Subordinate pass)

In the subordinate pass, coefficient is already found to be significant refined in magnitude. In the Subordinate pass, to understand the procedure for this pass, we use successive approximation [9]. For this, lets us take an example of 8*8 matrix. The example data using Morton scan order is shown in Figure 2.

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Example: 8*8 matrix

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127	69	24	73	-3	-5	34	
			67				
-37	-18	18	8	-1	0	-1	
			76				
44	87	15	21	-5	-4	64	
			32				
65	18	29	56	33	34	-10	
			15				
-33	52	56	68	-5	15	-2	
			15				
62	72	-34	-13	-4	-3	-2	-
			1				
-12	-26	5	-61	0	1	8	
			0				
-3	98	68	87	0	-1	7	
			1				

Figure 2: The Example Data Using Morton Scan Order [11]

127 is the maximum number in this matrix.

Max. value =127

To= 127/2 = 63.5

To ≥[Xmax/2]

Initial Threshold To =64

In 8*8 matrix we have a value 127, initially in first pass band this value is 64 or we can say threshold is 64.64 is significant so we say that its positive sign having a value equal to 1, here 1 means it is in the range on 64-127 because 64 is threshold. 69 is also lying in the range of 64-127.which is not significant is lying in the range of 0-63. In this case we are just subdivided into two such part. Now whichever is in the range of 64-127 we can encode them in 96 and 0-63 is encode as 32. now in the next pass we identified 64-127 range, whether it is in the range of 64-95 and whether it is in the range of 96-127 and then we approximate the value and that value is equal to min. of that range. it is successive approximation [11,23].

Step 4. New threshold

In this step we calculate the new threshold. If the minimum threshold or desired compression ratio is attained, we stop, if not repeat stage 2, 3 and 4.

SPIHT Algorithm

After performing the wavelet transform, SPIHT is used to encode the wavelet coefficients. SPIHT is refined version of EZW algorithm. SPIHT (set partitioning in hierarchical tree) achieve higher compression and better performance than EZW. SPIHT give better result of PSNR at higher compression ratio than EZW due to its partitioning property that increase its compressive power. The Flow Chart of SPIHT algorithm is shown in Figure 3.

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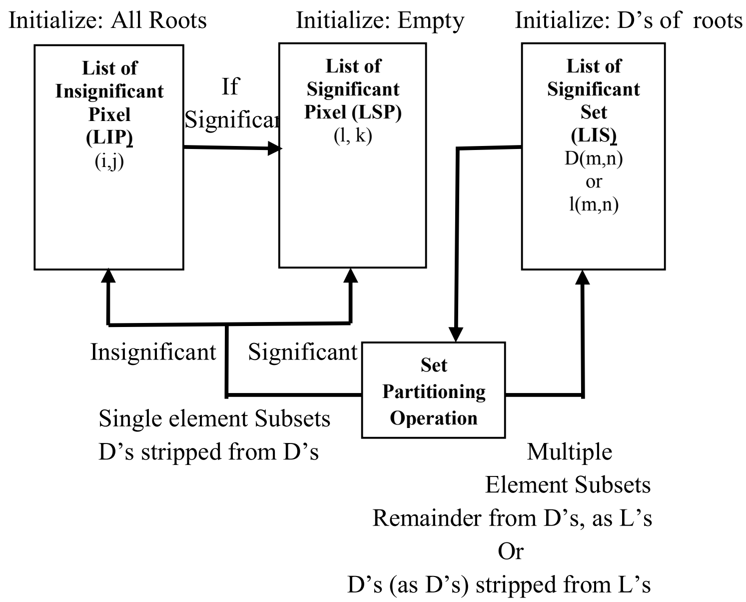

Figure 3: Flow Chart of SPIHT [11]

The Set Partition in Hierarchical Transform (SPIHT) technique involves 4 phases. These are initialization, sorting pass, refinement pass, and quantization-step update. In the first phase, empty the List of Significant Pixel (LSP). Now, add all coordinates from H to List of Insignificant Pixel (LIP). Another one type A entry consist descendants to List of Insignificant Set (LIS). In the 2^{nd} stages, each coordinates in LIS and LIP is given to significance test and output result comes in form of the code stream. D is the Set of all coordinates of the node (i, j). During the significance test, those that became significant in LIP is moved to LSP and those which are found to be significant in LIS are moved from the list and divided. The new subsets with more than one element are added to the LIS and the single pixels are added to LIP or the LSP, depending upon their significance. In the last stage, significant bits decrease rapidly and repeated until termination conditions is satisfied [11].

IV. MEASURING PARAMETER

The performance parameters are measured in terms of CR, PSNR and MSE.

A. Compression Ratio

Compression Ratio (CR) is the ratio between post compression file size and pre compression file size. For any algorithm compression Ratio (CR) should be higher [14].

$$\text{Compression Ratio} = \frac{\text{Size after Compression}}{\text{Size before Compression}} \quad (1)$$

B. Peak Signal to Noise Ratio (PSNR)

PSNR is defined as the ratio between maximum signal power to noise encountered in signal. PSNR should be higher for any algorithm.

$$\text{PSNR} = 10 \log_{10} \frac{M \times N}{MSE^2} \quad | \text{ db} | \qquad (2)$$

Where M×N is the resolution of the uncompressed image [14].

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C. Mean Square Error (MSE)

Mean Square Error defined the Mean Squared Error between the compressed image and original image. MSE should be lower for any algorithm. If MSE is 0 that's mean compressed image is similar to uncompressed image and is given by

$$\text{MSE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [\, f'(i,j) - f\,(i,j)]^2 \quad (3)$$

f' (i , j) is function of compressed image and f (i ,j) is the function of original image [14].

V. CONCLUSION

Lossless compression is a new technique for reduction of data quantity without reducing the quality of an image. In this paper, the study of different lossless compression algorithm has been done according to their measuring parameter. From the study of various paper, it has been conclude that the SPIHT and EZW algorithm are better in measuring parameter PSNR, MSE and CR as compared with other lossless compression techniques. In this paper, it has been conclude that the CR and PSNR of SPIHT is higher than other techniques and MSE of SPIHT is less than other techniques.CR and PSNR of EZW is less than SPIHT but higher than other techniques and MSE of EZW is higher than SPIHT but less than the other techniques.

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