COMPARATIVE ANALYSIS OF DIGITAL IMAGE COMPRESSION WITH DIFFERENT WAVELETS USING ANN AND RLE

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Abstract: *Image compression helps in fast data transfer and effective memory utilization. The objective of image compression is to reduce data redundancy of the image while retaining high image quality. This paper describes an approach for wavelet based image compression using Multi Layer Feed Forward Neural Network with Error Back Propagation training algorithm applied to second and third level approximation component and modified Run Length Coding is applied to second and third level Horizontal and vertical components and threshold is used to discard insignificant coefficients. The experimental results on several images indicate that the proposed algorithm is superior to the existing algorithm in terms of Compression Ratio (CR) by 30% to 40% with different wavelets.. The performance of the proposed algorithm is also compared with different discrete wavelet transform (DWT) techniques.*

Keywords: *Image Compression; Neural Network; Run Length Coding; discrete wavelet transform*

1.Introduction

Present day, the use of digital cameras, scanners and camera phones is increasing day by day. Capturing, storing and transmitting of the images have become a routine experience. In addition, imaging is extensively used in medicine, law enforcement, Internet gaming and data collected by satellites. Despite rapid improvements in data storage, processing speeds, and digital communication system performance, this proliferation of digital media often outstrips the amount of data storage and transmission capacities. Thus, the compression of such signals has assumed great importance in the use, storage and transmission of digital images. Many transform based Image compression techniques are evolved like DWT, LWT, DCT, SVD, DWT-DCT, and DWT-SVD [1]. Wavelets are superseding the DCTs [2]. This paper gives a comparative analysis of wide varieties of wavelets used to compress the image. These results are helpful to the community working on image compression.

2. Compression

The Proposed method is a blend of Neural Networks and Run length Coding.

2.1 Multi Layer Feed Forward Neural Network:

Approximation Component of the decomposed image is applied to neural network. In this proposed method, we have used a Multilayered Feed Forward Neural Netowrk. Having an input layer, a hidden layer and the output layer. Error back Propagation Algorithm is used for weights updation. The output of the hidden layer will give the compressed image. Other details of the Neural Network are given below. The number of neurons in the hidden layer are chosen based upon the desired compression. As shown in Fig. 3, we have taken 8 hidden layers. The number of neurons in the output layer will be the same as that in the input layer (64 in this case). The input layer and output layer are fully connected to the hidden layer.

The weights of synapses connecting input neurons and hidden neurons and weights of synapses connecting hidden neurons and output neurons are initialized to small random values from say –1 to +1. Only the weights between the hidden layer and the output layer are required for reconstruction. So, the numbers of weights are [64 x 8] and number of bits used to represent them are [64 x 8 x 8]. The input layer uses sigmoid function.

2.2 Run Length Coding

Run Length coding with certain modification is applied to the Horizontal and vertical coefficients obtained on applying threshold. With modified run length coding, non zero values are taken in separate array. Now in the array containing original detail coefficients after applying threshold, non zero values are forced to value one. Then number of times zero value and one value repeated are stored in an array. Now instead of transmitting entire sequence array containing non zero values, the number of times zero and one are repeated and first two values of array containing zeros and ones and also the total number of specific detail coefficients is transmitted.

3. Proposed Compression method

3.1 Procedure

Variety of wavelet based compression schemes have been evolved in recent years [3]. In this method, the first step is, decomposing the given image into Approximation component and detailed components by using the wavelets. By using discrete wavelet transform (DWT), the first Level decomposition gives LL1, HL1, LH1 and HH1 components. Out of these first three are considered for compression. Similarly in the second level decomposition LL2, HL2, LH2 are useful for compression. LL2 is approximation component and HL2 and LH2 are the detail components of the image. The Principle of Compression involves applying the approximation component to the

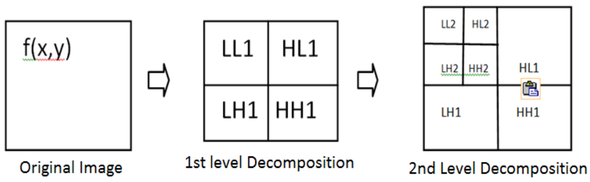

Fig.1. Approximation and detail components in 1st and 2nd level Decomposition

Multilayer feed forward neural network and detailed components will undergo run length coding.

The sub bands LH1 HL1 and HH1of first level and HH2 of second level are discarded. LL2 component is compressed by using MLNN. Before applying to the neural network LL2 component is subdivided into sub blocks of size p×p. p can be 8, then the block size is 8×8. This can be seen in fig. 3. All these non overlapping blocks are applied to neural network [4]. Compressed version of the image is obtained at the output of the hidden layer.

Threshold is applied to the HL2 and LH2 sub-bands to discard the insignificant coefficients as shown in fig. 2. The remaining coefficients are encoded using modified run length coding. In third level decomposition LL2 component is again divided into LL3, HL3, LH3 and HH3 components in a similar way. Higher levels can also be done [5]. Both the 2nd and 3rd level decompositions are shown in fig. 4. Level is limited to 3 to maintain the quality of reconstructed image. LL3 is applied to neural network and HL3 and LH3 are encoded in the same fashion using run length coding. The combination of the neural network and the run length coded outputs will give the compressed image.

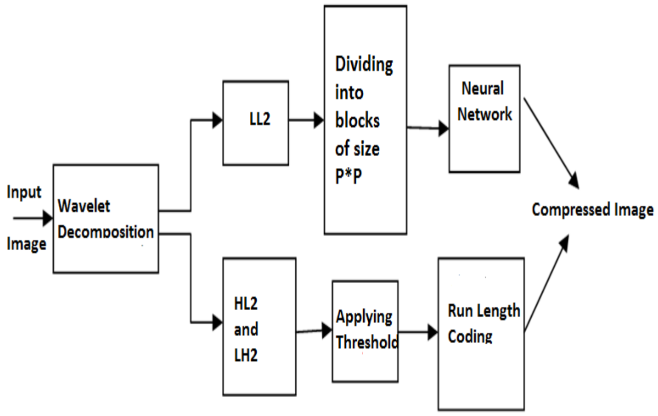

Fig. 2. Block diagram showing the method involved in the image compression.

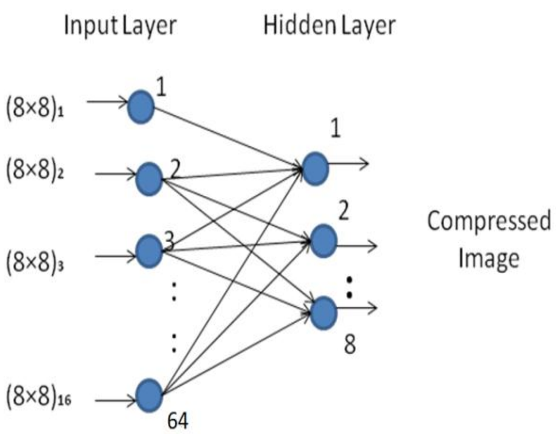

Fig. 3. Sub blocks of size 8×8 are applied, two layers are shown.

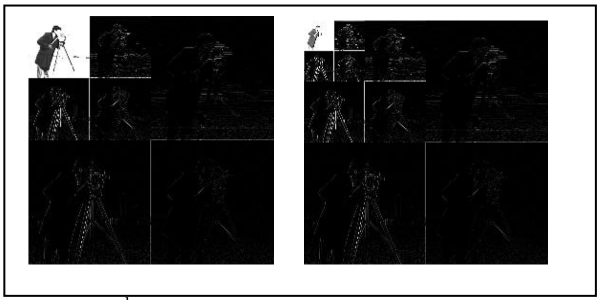

Fig. 4. a) 2nd Level and b) 3rd level decompositions of the image

Inverse Discrete Wavelet Transform (IDWT) is applied on the compressed image to reconstruct the original image.[6]

The compressed and reconstructed images for second level and third level decompositions are respectively shown in fig.5 and fig.6.

3.2 Algorithm for the Proposed Method

1. Reading the image from database.
2. Applying the wavelet on the image.
3. Discarding the sub bands LH1, HL1, HH1 and HH2 for 2nd level decomposition.
   (or) Discarding the sub bands LH1, HL1, HH1, LH2, HL2, HH2, HH3 for 3rd level decomposition.
4. Apply threshold to HL2 and LH2 sub bands to discard insignificant coefficients.(for 2nd level) (or)
   Apply threshold to HL3 and LH3 sub bands to discard insignificant coefficients.(for 3rd level)
5. Encode the threshold coefficients using modified run length coding.
6. Divide LL2 in to sub blocks of size p×p and apply to to the neural network for training.
7. The output of the hidden layer and modified run length encoded sequence gives the compressed image.

4. Experimental Results

4.1 Calculations and Measures

We have used Compression Ratio (CR), Mean squared Error (MSE), and Peak Signal to Noise Ratio (PSNR) as a measure of the quality of reconstructed image. Formula for Compression Ratio (CR) that we used in calculation is given in (i).

$$CR = 100 - \frac{Compressed\,ImageSize}{Origianal\,ImageSize} \times 100 \qquad \text{(i)}$$

Compressed image size in case of 2nd level decomposition at the output of NN hidden layer is 64×64. Hence irrespective of the type of wavelet, the compression ratio is fixed to 93.75. Similarly for 3rd level decomposition it is 98.4375.

For an M×N image the expressions to calculate the Mean Square Error (MSE) and the Peak Signal to Noise Ratio. (PSNR) are given in (ii) and (iii).

$$MSE = \frac{1}{MXN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j} - y_{i,j})^2 \qquad \text{(ii)}$$

$$PSNR = 10\log_{10}\left[\frac{(255)^2}{MSE}\right] \qquad \text{(iii)}$$

Here, $x_{i,j}$ is the input image and $y_{i,j}$ is the reconstructed image. As we have considered the pixel depth to be 8, we take 255 in the numerator to calculate PSNR.

4.2 Comparative Analysis

Table 1 shows the comparative analysis of different wavelets in compressing the 256×256 image cameraman.tif. Results are compared with quality assessing parameters such as CR, PSNR, MSE for NN to compress the image. This is done with symlets, biorthogonal, haar, coiflets and daubechies. Elapsed time (not shown in tables) is the taken for the neural network to finish the assigned task of compressing the approximation component (LL2 or LL3, depending on the level of decomposition). The time taken to compress the image using 2nd level is approximately three to four times to that of the 3rd level decomposition time. This is true with all the wavelets.

Reconstruction of the image is done with simple technique of inverse discrete wavelet transform. The reconstructed figures with sym4 wavelet are also shown in fig. 5 and fig. 6. The reconstructed image with 2 level decomposition has the PSNR of 72.0166db and MSE is 0.0041 as shown in Table 1. This is the maximum PSNR and MSE values obtained among all other symlets. However, even better values are obtained with db4 wavelet. For db4 wavelet, PSNR is 72.1732db and MSE is 0.0039. This is the best among all other wavelets used for the

Table 1. Comparison with different Wavelets

Wavelet	**Level**	**CR (100- %)**	**PSNR**	**MSE**
Sym2	2	93.7500	70.9317	0.0052
	3	98.4375	60.8801	0.0531
Sym3	2	93.7500	69.7836	0.0068
	3	98.4375	59.6036	0.0712
Sym4	2	93.7500	72.0166	0.0041
	3	98.4375	60.9081	0.0528
Sym5	2	93.7500	71.4174	0.0047
	3	98.4375	60.9054	0.0528
Bior6.8	2	93.7500	64.6624	0.0222
	3	98.4375	57.5098	0.1154
Coif1	2	93.7500	65.8649	0.0168
	3	98.4375	58.5148	0.0915
Coif2	2	93.7500	65.6844	0.0176
	3	98.4375	58.4856	0.0922
Haar	2	93.7500	70.9980	0.0052
	3	98.4375	60.9499	0.0523
Db1	2	93.7500	70.9983	0.0052
	3	98.4375	60.9490	0.0523
Db2	2	93.7500	70.9320	0.0052
	3	98.4375	60.8796	0.0531
Db3	2	93.7500	69.9878	0.0065
	3	98.4375	60.6489	0.0560
Db4	2	93.7500	72.1732	0.0039
	3	98.4375	60.9802	0.0519
Db5	2	93.7500	71.9008	0.0042
	3	98.4375	60.9496	0.0523
Db6	2	93.7500	68.0676	0.0101
	3	98.4375	60.0091	0.0649
Db7	2	93.7500	67.6653	0.0111
	3	98.4375	59.8154	0.0678
Db8	2	93.7500	67.1900	0.0124
	3	98.4375	59.6030	0.0712

image compression and reconstruction. Haar wavelet is same as the db1. This can be very clearly seen from the values obtained for both of the wavelets. In both cases PSNR is 70.998 db and MSE is 0.0052. All These facts can be observed from Table IV and V, which shows that the values obtained in Table I are true with other images also.

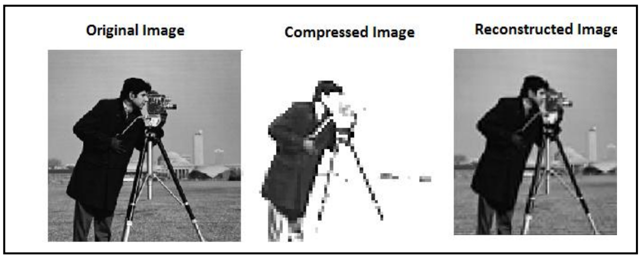

Fig. 5. Cameraman image with Second Level Decomposition

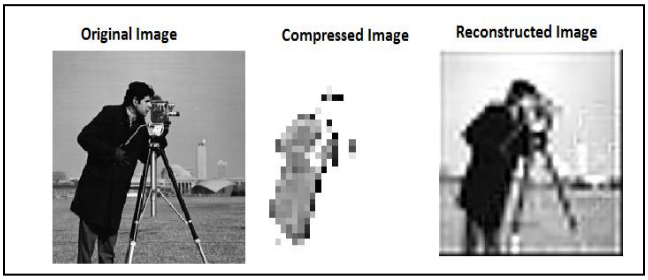

Fig. 6. Cameraman image with third Level Decomposition

The Compression Ratio obtained for 3rd level method is 98.4375. Compressed and reconstructed images are shown in Fig. 6. Reconstructed image is blur having a MSE of 0.0528 and PSNR is 60.9081db with sym4. are listed in the Table I

We have shown the better technique which compresses the image to almost 98%. However Image enhancement techniques are still needed for the improvement of the reconstructed image. For this proposed third level decomposition of the image, the best suited wavelets are db4, sym4, db5, mparison of different wavelets sym5, db1 or Haar[7]. Out of all the biorthogonal wavelets bior6.8 alone suits for these 256×256 images Cameraman, TT, and vk. Only that are suitable out of all coiflets, symlets and daubechies for these images[8][9][10]. Coiflets and Bior6.8 gave poor performance compared to the remaining wavelets both in terms of PSNR and MSE.

Table 2. Comparison with existing method I.

	MSE	PSNR	CR
PROPOSED	**0.0022**	**74.7560**	**93.75**
EXISTING	0.0063	70.1602	27.8995
SPIHT	25.33	34.09	5.95
EZW	46.11	31.49	3.07
SOFM	73.72	29.45	8.92

Table 3. Comparison with existing method II.

Wavelet	Level	CR (100- %) Existing method2	CR (100- %) Proposed method	Improvement (%)
Haar	2	63.1034	93.7500	30.6466
	3	64.3912	98.4375	34.0463
Coif1	2	56.0988	93.7500	37.6512
	3	57.6426	98.4375	40.7949
Coif2	2	57.0760	93.7500	36.674
	3	58.4245	98.4375	40.013

Table 4. Results with 'TT' Image

Wavelet	Level	CR (100- %)	PSNR	MSE
Sym4	2	93.7500	74.0851	0.0025
	3	98.4375	60.8690	0.0532
Sym5	2	93.7500	73.1836	0.0031
	3	98.4375	60.8592	0.0534
Db5	2	93.7500	73.8737	0.0027
	3	98.4375	60.8947	0.0529
Db4	2	93.7500	74.5930	0.0023
	3	98.4375	60.9397	0.0524
Haar	2	93.7500	73.1968	0.0031
	3	98.4375	61.0203	0.0514

In SOFM, the CR and the quality of reconstructed image are poor [5]. SPIHT and Embedded Zero Wavelet [8] gives an acceptable visual quality but with poor compression ratio. Proposed method with sym4 wavelet is even better to the similar existing method given in [5], which is clearly shown in Table II. All results shown in Table II are for a 512×512 lena.jpg image. Proposed method gave better results compared to other existing method [7] in terms of CR. With Proposed method, 30% to 40% improvement in CR is observed as shown in Table III.

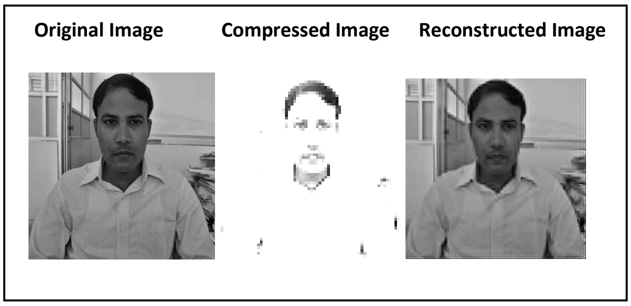

Fig. 7. 'TT' image with Second Level Decomposition

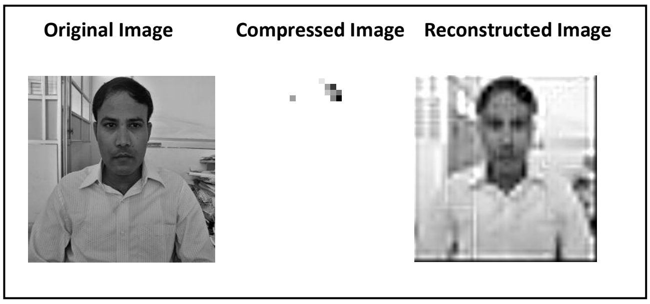

Fig. 8. 'TT' image with Third Level Decomposition

Table 5. Comparison with 'vk' image

Wavelet	Level	CR (100- %)	PSNR	MSE
Sym4	2	93.7500	74.059	0.0026
	3	98.4375	60.428	0.0589
Sym5	2	93.7500	72.914	0.0033
	3	98.4375	60.422	0.0590
Db5	2	93.7500	73.874	0.0027
	3	98.4375	60.506	0.0579
Db4	2	93.7500	74.592	0.0023
	3	98.4375	60.547	0.0573
Haar	2	93.7500	73.196	0.0031
	3	98.4375	60.406	0.0592

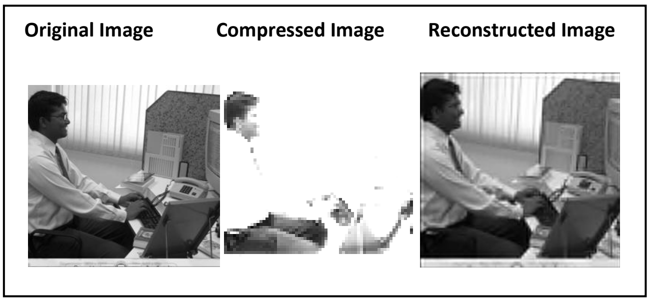

Fig. 9. 'Vk' image with Second Level Decomposition

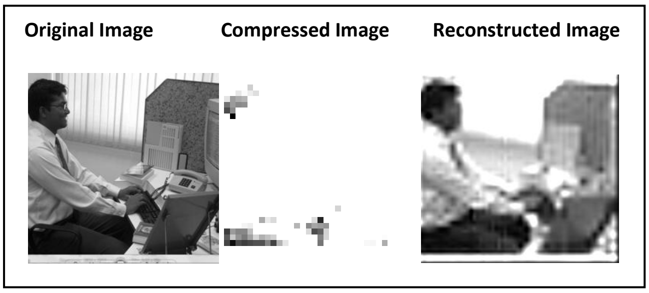

Fig. 10. ‘Vk’ image with Third Level Decomposition

5.Conclusion

In this paper, Compression principle is clearly explained. Both the 2nd level and 3rd level decompositions are compared with the figures of the compressed and reconstructed images. CR, PSNR, MSE for NN are compared with different wavelets and are shown in Tables. It is found that Haar is better compared to coiflets as stated in [7]. Symlet families of wavelets are better compared to the coiflet family. Haar results are satisfactory with symlets sym 4, sym 5 and daubechies db1 to db5. From db6 to db8 PSNR and MSE values show that the reconstructed image is degrading. Only Bior 6.8 is suitable with this method among the biorthogonal wavelets for these images. The values obtained in Tables IV and V assures these facts. Moreover, proposed method is superior to the existing method by 30% to 40% with different wavelets as shown in Table III in terms of CR.

References

1. D.P. Dutta, S. D. Choudhury *“Digital Image compression Using” 2009 International Conference on Advances in computing , control and Telecommunication Technologies*. ACT 09, 28-29 Dec 2009
2. Rohit Arora et al, *“An Algorithm for Image compression using 2D wavelet Transform” International Journal of Engineering science and Technology(IJEST)*, Vol 3, No. 4, Apr 2011.
3. Rafel C. Gonzalez, Richard E.Woods *Digital Image Processing* 2nd edition.
4. J. Villasenor, B. Belzer, J.Liao, *“Wavelet Filter Evaluation for Image Compression,” IEEE transactions on Image processing,* Vol 2, pp. 1053-1060, August 1995.
5. P Srikala, Shaik Umar Faruq *Neural Network based Image Compression with Lifting Scheme and RLC IJRET*, Volume 1, Issue 1, pp 13-19.
6. K. Kannan, S. Arumuga Perumal*: Optimal level of decomposition of stationary wavelet transform for region level fusion of multifocused images. ICTACT JOURNAL ON IMAGE AND VIDEO PROCESSING,* November 2010, ISSUE: 02 pp 76-79.
7. *S*andeep kaur, Gaganpreet Kaur, Dr.Dheerendra Singh *Comparative Analysis Of Haar And Coiflet Wavelets Using Discrete Wavelet Transform In Digital Image Compression* IJERA Vol. 3, Issue 3, May-Jun 2013, pp.669-673
8. S.P. Raja, Dr. A. Suruliandi *“Analysis of Efficient Wavelet based Image Comppression Techniques” 2010 Second International Conference on Computing, Communication and Networking Technologies.*
9. James S. Walker., *A Primer on Wavelets and Their Scientific Applications,* second edition, Taylor& Francis Group LLC, Beijing Jun. 2008.
10. by Esak kiranjan S, Veera Kumar T, Jayaraman *Digital Image Processing MGH Internation*