Performance Analysis of Daubechies Wavelet and Differential Pulse Code Modulation Based Multiple Neural Networks Approach for Accurate Compression of Images

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Abstract

Large Images in general contain huge quantity of data demanding the invention of highly efficient hybrid methods of image compression systems involving various hybrid techniques. We proposed and implemented a Daubechies wavelet transform and Differential Pulse Code Modulation (DPCM) based multiple neural network hybrid model for image encoding and decoding operations combining the advantages of wavelets, neural networks and DPCM because, wavelet transforms are set of mathematical functions that established their viability in the areas of image compression owing to the computational simplicity involved in their implementation, Artificial neural networks can generalize inputs even on untrained data owing to their massive parallel architectures and Differential Pulse Code Modulation reduces redundancy based on the predicted sample values. Initially the input image is subjected to two level decomposition using Daubechies family wavelet filters generating high-scale low frequency approximation coefficients A2 and high frequency detail coefficients H2, V2, D2, H1, V1 and, D1 of multiple resolutions resembling different frequency bands. Scalar quantization and Huffman encoding schemes are used for compressing different sub bands based on their statistical properties i.e the low frequency band approximation coefficients are compressed by the DPCM while the high frequency band coefficients are compressed with neural networks. Empirical analysis and objective fidelity metrics calculation is performed and tabulated for analysis.

Keywords: Backpropagation, Daubechies Wavelet, DPCM, PSNR, MSE, Neural Networks.

1. INTRODUCTION

The growing energy requirements of wireless data services, biomedical applications, computer graphics and many other web based applications disclosed an urge to innovate new techniques in the areas of signal and image processing to compress and decompress signals as well as still images and videos of various types and sizes to meet the everlasting storage space and channel bandwidth requirements. Wavelets perform better and provide good compression ratios for high resolution images relative to other competing technologies like JPEG objectively and subjectively as well. Unlike JPEG, wavelet does not show any blocking effects and allow degradation of the whole image quality while preserving the significant details of an image [1].The rapid development of high performance computing and communications opened up tremendous opportunities in the development of different telecommunication applications, Image compression is the context where images of different sizes are compressed using different methodologies to meet demand for ever growing bandwidth requirements.

Since Images can be regarded as two dimensional signals, many digital Image compression techniques for one dimensional signal are extended to 2-D images to exploit the correlations between the neighboring pixels to eliminate the redundancies. Traditional techniques of compression aims at reducing the Coding, Interpixel and Psycho visual redundancies, [2] additionally new soft computing technologies like Neural Networks are developed for image compression owing to their features of Parallelism, Learning capabilities, Noise Suppression, Transform extraction and Optimized Approximations which encouraged researchers to use multiple combination techniques of wavelets and neural networks for image compression applications.

Image compression techniques are basically Lossy and Lossless.Lossless image compression techniques encode data exactly such that decoded image is almost identical to original image but they are limited in terms of compression ratio [3]. Few lossless image compression techniques are

i) Run Length encoding

ii) Huffman encoding

iii) LZW coding

iv) Area coding

Lossy image compression techniques encode an approximation of original image with good compression ratios and less distortion in the reconstructed image. Lossy compression techniques include transform coding, quantization and entropy encoding operations, In transform encoding input image is mathematically transformed by separating image information on gradual spatial variation of brightness from regions with faster variations in brightness at edges of the image [3][4] Few lossy compression techniques are:

i) Transformation Coding techniques

ii) Vector quantization

iii) Fractal coding

iv) Block Truncation coding

v) Sub band coding

The proposed methodology of hybrid compression is a combination of both the lossy compression and lossless compression techniques.

This paper is organized as follows. Section 2, briefs the objective fidelity design metrics. Section 3, explains the Daubechies wavelet transform and Differential Pulse Code Modulation. In section 4, neural networks and backpropagation algorithm for training them are discussed. Section 5, discusses the proposed hybrid methodology of image compression and decompression system. Section 6, elaborates the Experimental results. Section 7 discusses the conclusion reached by analysis.

2. DESIGN METRICS

Digital image compression techniques are normally analyzed with objective fidelity measuring metrics like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Compression Ratio (CR), Encoding time, Decoding time and Transforming time etc[2][5].

2.1 Mean Square Error (MSE)
MSE for monochrome images is given by

$$\frac{1}{N^2}\sum_{i}^{N}\sum_{j}^{N}[X(i,j)-Y(i,j)]^2 \qquad (1)$$

MSE for color images is given by

$$\frac{1}{N^2}\sum_{i}^{N}\sum_{j}^{N}\{[r(i,j)-r^*(i,j)]^2+[g(i,j)-g^*(i,j)]^2+[b(i,j)-b^*(i,j)]^2\} \qquad (2)$$

Where r (i, j), g (i, j) and b (i, j) represents the color pixels at location (i, j) of the original image. r* (i, j), g* (i, j) and b*(i, j) represent the color pixel of the reconstructed image, while N x N denotes the size of the pixels of the color images [2]

2.2 Peak Signal to Noise Ratio (PSNR)
Peak signal to Noise Ratio is the ratio between signal variance and reconstruction error variance. PSNR is usually expressed in Decibel scale. The PSNR is a most common measure of the quality of reconstructed image in case of image compression.

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \qquad (3)$$

Here 255 represent the maximum pixel value of the image, when the pixels are represented using 8 bits per sample. PSNR values range between infinity for identical images, to 0 for images that have no commonality. PSNR is inversely proportional to MSE and compression ratio i.e PSNR decreases as the compression ratio increases.

2.3 Compression Ratio (CR)
Compression ratio is defined as the ratio between the original image size and compressed image size.

$$Compression\,Ratio = \frac{Original\,Image\,Size}{Compressed\,Image\,Size} \qquad (4)$$

3. COMPRESSION TECHNIQUES
3.1 Wavelet Transforms
Wavelet transforms allow good localization in frequency and space, Wavelet transforms represent image as a sum of wavelet functions with different locations and scales [18]. Wavelet transforms are continuous and discrete. Continuous wavelet transforms are time consuming for long signals, as the signal needs to be integrated at all times. Discrete wavelet transform (DWT) is implemented through sub band coding, it can localize signals in time and scale, the scaling operation is done by changing the resolution of signal through sampling [10].

Often signal processing in time domain require frequency related information, Mathematical transforms translate the information of signals into different forms. For example the Fourier transforms converts the signals in both time domain and frequency domain, but they failed to provide time specific frequency information however in Short Term Fourier Transform (STFT) window based technique, different parts of the signal can be viewed specifically [13]. But in accordance with the Heisenberg's Uncertainty Principle, resolution gets worse in frequency domain, if it is improved in time domain by zooming different sections. The power of wavelets comes from the use of multiresloution i.e. different parts of the wave are viewed through different sized windows where high frequency parts in the signal use smaller windows to give good time resolution while the low frequency parts use big windows to extract frequency information [5].

In case of wavelet decomposition,wavelet function represent the high frequency detail parts clearly showing the Vertical, Horizontal and Diagonal details of the image while the scaling function represent the low frequencies or smooth parts of the image clearly corresponding to the approximation coefficients. If the number of high frequency coefficients are smaller than the threshold values they can be set to zero without significantly changing the image, If the number of zeros are greater, large compression can be achieved. If the threshold value is set to zero, then the energy or the amount of information retained is 100% and the compression is said to be lossless as the image can be reconstructed exactly. However, as more zeros are obtained more energy is lost; hence a balance is required [18].

3.1.1 Daubechies Wavelets

A major problem in the development of wavelets during the 1980's was the search for scaling functions that are compactly supported, orthogonal and continuous. These scaling functions were first constructed by Ingrid Daubechies, this construction amounts to finding the low pass filter h, or equivalently, the Fourier series. Ingrid Daubechies invented compactly supported orthonormal wavelets- thus making discrete wavelet analysis practicable [20].

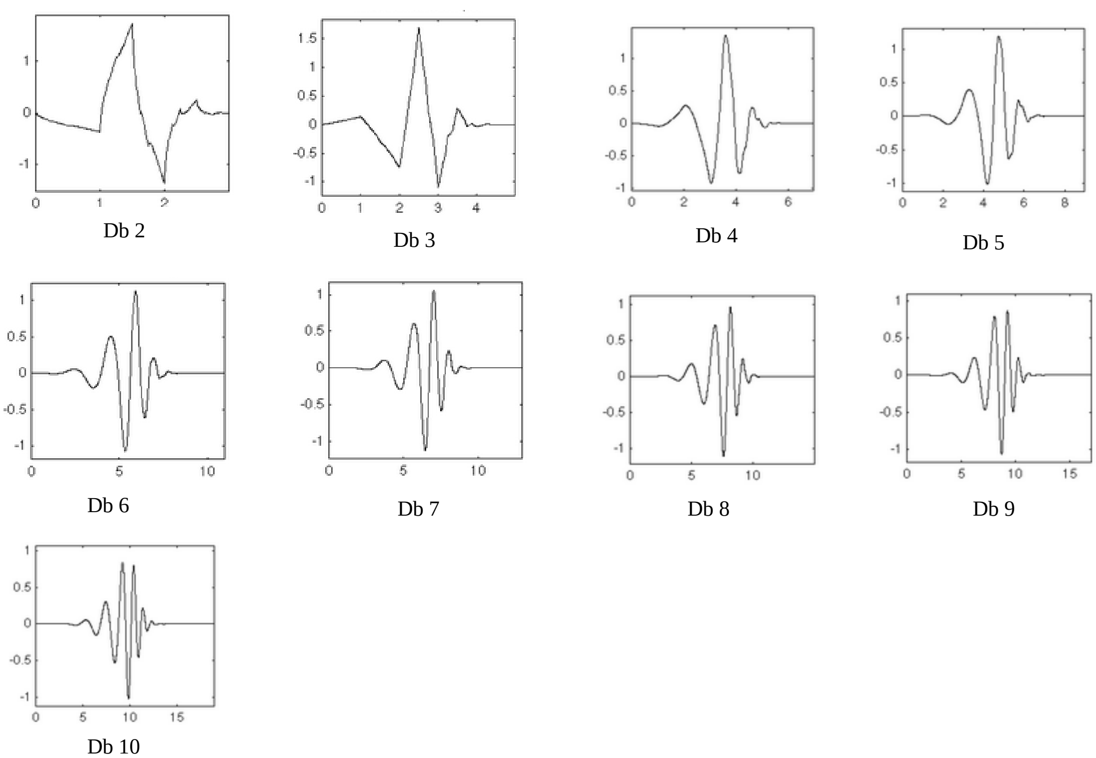

FIGURE 1: Wavelet Functions of Daubechies.

Daubechies wavelet transform signal is defined by the scaling and wavelet functions that are expressed in terms of α and β coefficients, respectively. Daubechies 1 represents same wavelet as Haar wavelet.

$$\alpha_1 = \frac{1+\sqrt{3}}{\sqrt[4]{2}} \quad (5) \qquad \alpha_2 = \frac{3+\sqrt{3}}{\sqrt[4]{2}} \quad (6)$$

$$\alpha_3 = \frac{3+\sqrt{3}}{\sqrt[4]{2}} \quad (7) \qquad \alpha_4 = \frac{1+\sqrt{3}}{\sqrt[4]{2}} \quad (8)$$

Daubechies wavelet transforms are defined similar to the Haar wavelet by obtaining running averages and differences through scalar products with scaling signals and wavelets. For high order Daubechies wavelets DbN, N denotes the order of wavelet and the number of vanishing moments, Daubechies wavelets have the highest number (A) of vanishing moments for given support width N=2A,The length of the wavelet transform is easy to put into practice using the fast wavelet transform, the approximation and detail coefficients are of length[16] [21].

$$\text{Floor}\left(\frac{n-1}{2}\right) + N \qquad (9)$$

If n is the length of f (t), this wavelet has balanced frequency responses but non-linear phase responses. Wavelets with fewer vanishing moments give less smoothing effects and remove less details, but wavelets with more vanishing moments produce distortions. Daubechies wavelets are widely used to solve broad range of problems like for example, self-similarity Properties of a signal or fractal problems, signal discontinuities etc. The wavelet functions of Daubechies family are listed in fig.1, in which x-axis represents the time and y-axis represents the frequency.

3.2 Differential Pulse Code Modulation

Differential pulse code modulation (DPCM) [14] [15] is a signal encoder that uses the baseline of pulse code modulation (PCM) but adds some functionality based on the prediction of signal samples.Input to a DPCM is an analog or digital signal. If the input is a continuous time analog signal, it needs to be sampled first so that a discrete time signal is the input to the DPCM encoder. In DPCM, We transmit the difference e (n), between x (n) and its predicted value y (n) but not the present sample x (n). At the receiver, we generate y (n) from the past sample value to which the received x (n) is added to generate x (n). There is, however, one difficulty associated with this scheme. At the receiver, instead of the past samples x (n-1), x (n-2)… as well as e(n), we have their quantized version xs (n-1), xs (n-2),… This will increase the error in reconstruction. In such a case, a better strategy is to determine y (n), the estimate of x_s (n) (instead of x (n), at the transmitter also from the quantized samples x_s(n-1), x_s(n-2),… The difference e (n)=x (n)-y (n) is now transmitted via PCM. At the receiver, we can generate y (n), and from the received e (n), we can reconstruct x_s(n). [16]

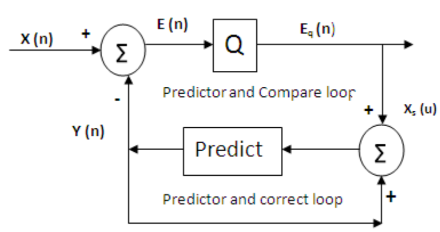

FIGURE 2: DPCM Encoder.

The difference of the original image data, x (n), and prediction image data, y(n) is called estimation residual, e(n). So

$$\mathbf{e\ (n) = x\ (n) - y\ (n)} \qquad (10)$$

Is quantized to yield

$$e_Q(n) = x(n) + q(n) \quad (11)$$

Where q (n) is the quantization error and eq (n) is quantized signal and

$$q(n) = e_q(n) - e(n) \quad (12)$$

$$q(n) = \frac{I_{max}}{2^b} = \frac{(simg)_{max}}{2^b} \quad (13)$$

Here b is number of bits. Imax (Simg) max is maximum value of an image signal. The prediction output y (n) is fed back to its input so that the predictor input x_s (n) is

$$x_s(n) = y(n) + e_q(n) \quad (14)$$

$$= x(n) - e(n) + e_q(n)$$

$$= x(n) + q(n)$$

This shows xs (n) is quantized version of x (n). The prediction input is indeed xs (n), as assumed [19].

4. Artificial Neural Networks and LM Algorithm

Artificial neural networks pre-process the input patterns to produce patterns of sufficient compression rates preserving the information security [6]. An artificial neural network is a nonlinear system and powerful data modeling tool meant for solving optimization problems. Few advantages of neural networks are, they are self adaptive and adjust themselves to the data, they approximate any function with arbitrary accuracy, they are fault tolerant via redundant information coding, and can retain their capabilities despite major network damage with minimum degradation in the performance. Finally, neural networks model the real world complex relationships [7].

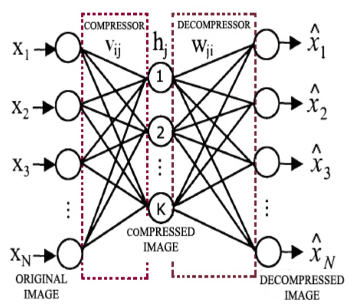

FIGURE 3: Basic Image Compression using ANN.

In case of a multilayered perceptron (MLP)type feed forward neural network architecture, number of connections between any two layers is the summation of number of bias neuron connections of the second layer (bias connections of a layer is equal to the number of layer neurons) and product of total number of neurons in the two layers. If there are N_i neurons in the input layer, N_h neurons in the hidden layer and N_o neurons in the output layer, total number of connections are given by the equation:

Network Size $:(N_w) = [(N_i * N_h) + N_h] + [(N_h * N_o) + N_o]$ (15)

Levenberg-Marquardt (Backpropagation) algorithm [4] is a common supervised training methods used for training the artificial neural networks which is based on error-correction learning rule. Here the error propagation through the network involves a forward pass and a backward pass. In the forward pass the synaptic weights of the network are fixed, however, in the backward pass the synaptic weights are adjusted in accordance with an error-correction rule. The Network is trained by iterative updation of weights to minimize the mean square error. [8] The computed error signal is then propagated backward to the lower layers and the synaptic weights of the network are adjusted accordingly such that the error is decreased along the descent direction to move the actual response of the network closer to the desired response. In case of neural networks with more than one hidden layer, backpropagation algorithm converges slowly, as the output is saturated due to the activation function used, and the descent gradient takes a very small value, even if the output error is large, leading to a little progress in the adjustment of weights. Learning rate and momentum factor are two parameters used for weights adjustments in the direction of the descent to suspend oscillations [9].

5. IMAGE COMPRESSION/ DECOMPRESSION SYSTEM

The proposed architecture analyses the performance of Daubechies wavelet and Differential Pulse Code Modulation based hybrid model using multiple neural networks for accurate compression of images. Scalar quantization and Huffman encoding are also used as well to eliminate the psychovisual and coding redundancies. Initially, the selected standard input image is compressed by decomposing it twice using Daubechies (Db10) filter wavelet transforms to generate the low frequency band approximation coefficients and the high frequency band detail coefficients clearly showing the horizontal, vertical and diagonal details of the image after the two levels of decomposition. The low frequency approximation coefficients in the second level are now compressed using differential pulse code modulation encoder while the high frequency band coefficients after both levels of decomposition are compressed in a parallel arrangement of artificial neural networks of dimensions M-N-P where M, N, P represent the number of artificial neurons in the Input layer, Hidden layer and the Output layer. Further compressed hidden layer outputs of the five proposed neural networks are scalar quantized together and Huffman encoded in combination with the DPCM output, this operation generates the overall compressed image output. Decompression process involves the reverse operations of Huffman decoding, reverse quantization; decompression in neural networks between hidden and output layers of the respective neural networks, inverse DPCM operation or DPCM decoding and inverse Dabechies filter wavelet transform operations to retrieve the reconstructed image.

Bench mark images circuit, lifting body, rice, testpat1 and Lena of different sizes ranging from 256 x 256 pixels down to 32 x 32 pixels are considered for analysis.

5.1 Image Encoding Scheme

Initially the selected bench mark image of size 256 x 256 is decomposed first using Daubechies filter wavelet transform(Db2) to generate low frequency approximation coefficients A1 and three high frequency detail coefficients H1, V1, D1 of resolutions 128 X 128 each,after the first level of decomposition. The first level approximation coefficients so obtained are now decomposed at the second level generating approximation coefficients A2 and three detail coefficients H2, V2, D2, of resolutions 64 x 64 giving rise to a total of seven frequency bands after two level decomposition.
The first band high-scale low frequency approximation coefficients A2 contain significant information while the low-scale, high frequency detail coefficients represent the second, third and fourth bands respectively. Band1 low frequency approximation coefficients A2 are now compressed using DPCM to reduce the inter pixel redundancy; DPCM predicts the value of neighboring pixel based on the previous pixel information, the difference between current pixel and predicted pixel is then given to an optimal quantizer which reduces the granular noise and slope over load noise. Finally the error output is obtained from DPCM.

The second level decomposed low-scale, high frequency detail coefficients H2, V2, D2 are encoded using three different multi layer Perceptron type feed forward neural networks of dimensions 16-12-16. Similarly the first level decomposed low-scale, high frequency detail coefficients H1, V1 are encoded using two different MLP type feed forward neural networks of dimensions 16-8-16.Compression normally takes place between the input layer and hidden layer of the selected neural network; the compressed hidden layers coefficients at the outputs of the five different neural networks are scalar quantized, the quantized bits in combination with DPCM encoded data are further Huffman encoded to generate the compressed image, which can be stored for the purpose of transmisson .

In the entire process of encoding and decoding operations the first level decomposed low-scale, high frequency detail coefficients D1 are discarded for the current analysis since they contain no useful data. Throughout the analysis all the artificial neural networks are trained with error backpropagation algorithm or Levenberg-Marquardt algorithm.

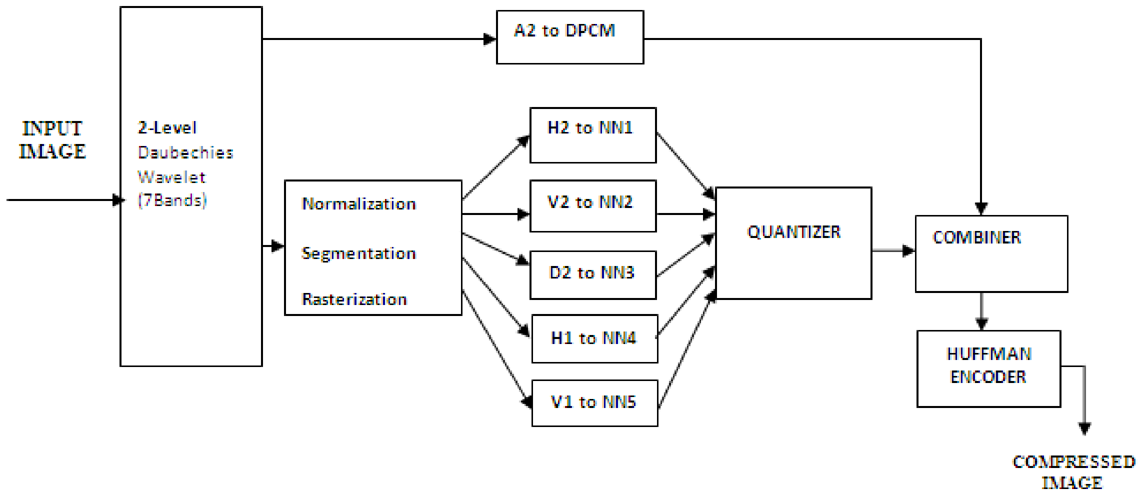

FIGURE 4: Proposed Image Compression System Architecture.

5.2 Image Decoding Scheme

In the decoding process as shown in Fig. 5, the compressed image coefficients are decoded in the Huffman decoder initially; the reconstructed bit streams are now split to separate the band1 high-scale low frequency approximation coefficients A2 and the remaining five bands of high frequency detail coefficients H2, V2, D2, H1 and V2. The compressed low frequency band-1 coefficients are now fed to the inverse DPCM unit for decoding operation while band 2 to band 6 high frequency detail coefficients are reverse quantized and fed to the output layers of respective neural networks for decoding purpose.Reconstructed sub band coefficients of inverse DPCM unit and neural networks are reconstructed with Inverse Daubechies filter Wavelet Transform (IDWT) operation to generate the desired reconstructed image.

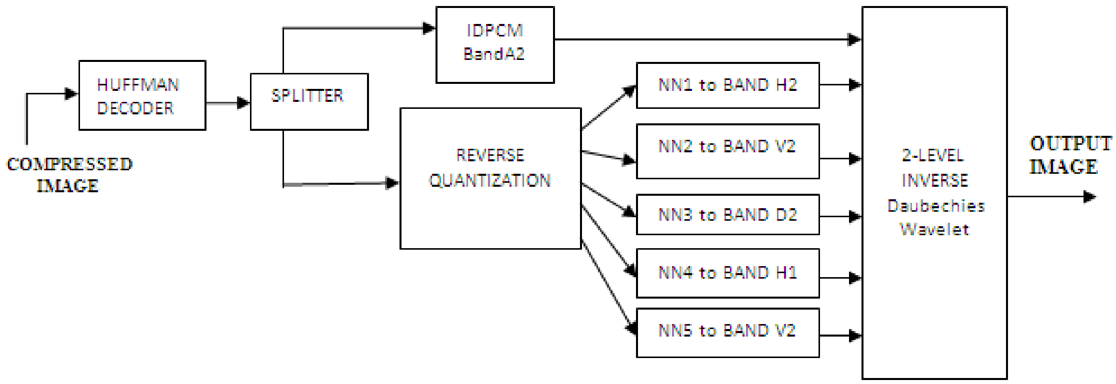

FIGURE 5: Proposed Image Decompression System Architecture.

6. EXPERIMENTAL RESULTS

Experiments are conducted on several standard bench mark images and the results of few of the images are presented here.

Figures 6-10, as shown below contain four different images in each figure. They are arranged in the order of top row and bottom row with two images in each row. They can be read as the original input image and 2-Level wavelet compressed image in the top row starting from the left, and the output image, error image in the bottom row from the left.

Measured objective fidelity metrics PSNR, MSE and CR for each image analysed after experimentation are tabulated for relative analysis purpose.

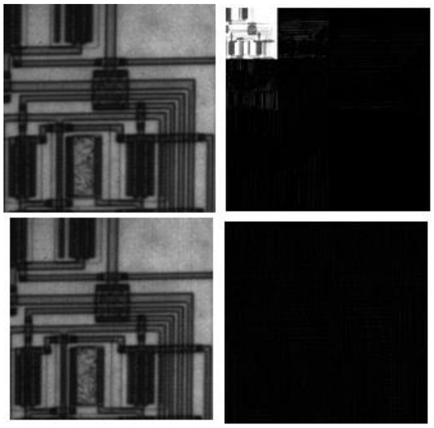

FIGURE 6: Circuit Image.

TABLE 1: Results of Cameraman Image.

Input Image	BAND	A2	H2	V2	D2	H1	V1
Circuit	NN Size		16-12-16	16-12-16	16-12-16	16-8-16	16-8-16
	Encoding Time	307.8511					
	PSNR	54.00	36.10	30.55	42.94	45.69	45.09
	MSE	0.25	15.92	57.23	3.29	1.75	2.01
	Overall PSNR	31.9580					
	Overall MSE	41.4267					

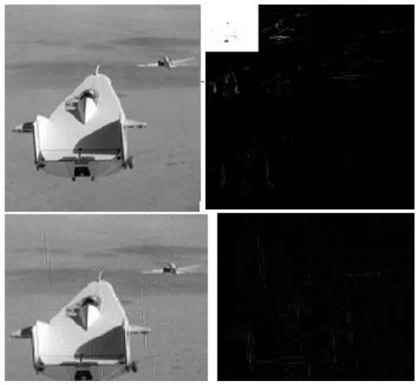

FIGURE 7: Lifting Body Image.

Table 2. Results of Lifting Body Image

Input Image	BAND	A2	H2	V2	D2	H1	V1
Lifting Body	NN Size		16-12-16	16-12-16	16-12-16	16-8-16	16-8-16
	Encoding Time	274.9183					
	PSNR	52.88	34.24	31.89	39.09	41.22	39.90
	MSE	0.33	24.44	42.04	8.01	4.90	6.64
	Overall PSNR	30.6541					
	Overall MSE	55.9337					

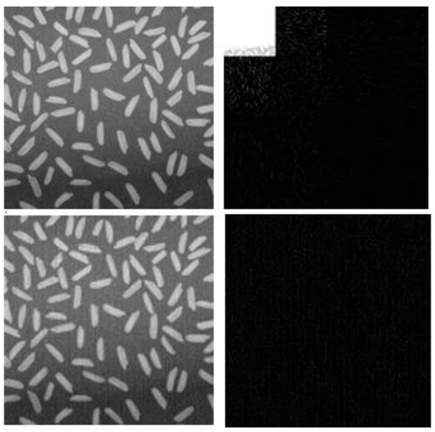

FIGURE 8: Rice Image.

TABLE 3: Results of Rice Image.

Input Image	BAND	A2	H2	V2	D2	H1	V1
Rice	NN Size		16-12-16	16-12-16	16-12-16	16-8-16	16-8-16
	Encoding Time	512.5771					
	PSNR	53.04	30.07	25.59	33.07	27.25	28.60
	MSE	0.32	63.96	179.24	32.06	122.26	89.73
	Overall PSNR	26.1428					
	Overall MSE	158.0532					

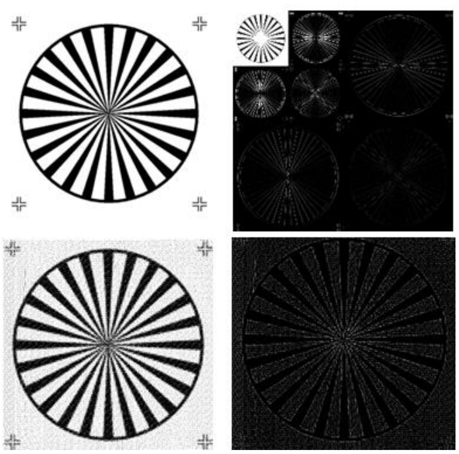

FIGURE 9: Testpat1 Image.

TABLE 4: Results of Testpat1 Image.

Input Image	BAND	A2	H2	V2	D2	H1	V1
TESTPAT1	NN Size		16-12-16	16-12-16	16-12-16	16-8-16	16-8-16
	Encoding Time	0.00214					
	PSNR	45.07	19.07	16.32	24.98	10.71	18.52
	MSE	2.022	803.75	0.005	206.38	0.005	913.7
	Overall PSNR	16.0276					
	Overall MSE	0.00162					

FIGURE 10: Lena Image.

TABLE 5: Results of Lena Image.

Input Image	BAND	A2	H2	V2	D2	H1	V1
LENA	NN Size		16-12-16	16-12-16	16-12-16	16-8-16	16-8-16
	Encoding Time	238.698					
	PSNR	51.27	26.96	29.98	35.43	39.61	35.98
	MSE	0.48	130.67	65.24	18.60	7.11	16.40
	Overall PSNR	23.9491					
	Overall MSE	261.921					

7. CONCLUSION

In proposed hybrid encoding and decoding scheme five bench mark input images Circuit, Lifting Body, Rice, Testpat1 and Lena of size 256 x 256 are tested and analysed for variations in objective fidelity metric measures PSNR, MSE, CR and Encoding time. It was observed that Circuit image produced better PSNR of order 31.958; Testpat1 image has the merit of being faster in performing the encoding operation and demerits of producing least PSNR and highest MSE values.When compared to neural networks based image compression techniques, Wavelet based image compression combined with DPCM and neural networks dramatically improve the quality of reconstructed images.

The proposed methodology can be explored to obtain better metrics with more number of hidden layers in the selected neural networks and varying the number of neurons in the hidden layers for training the network properly for early convergence. The proposed architecture can be tested with neural networks based on learning vector quantization and code book maintenanace technique, arithmetic coding instead of Huffman encoding technique etc. This work can be further extended to explore the possibilities of applying hybrid combination techniques for effective data, image and video compression also.

There are many other existing and new wavelet functions, whose combination with other methodologies can always create wonderful statistics.

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