ijecs open access www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 2 Issue 8 August, 2013 Page No. 2468-2475

IMPLEMENTATION OF WAVELET TRANSFORM, DPCM AND NEURAL NETWORK FOR IMAGE COMPRESSION

***V.Krishnanaik*[1] *Dr.G.Manoj Someswar*[2] *K.Purushotham*[3] *A.Rajaiah*[4]**

[1]Asst. Professor, Department of Electrical & Computer Engineering, College of Engineering & Tech, Aksum University,Axsum. *E-Mail: krishnanaik.ece@gmail.com,*
[2]Professor in CSED, Anwarul- uloom College of Engineering and Technology, Hyderabad. India.*E-mail: manojgelli@gmail.com*
[3]Asst. Professor, Department of Electrical & Computer Engineering, College of Engineering & Tech, Jigjiga University, Jigjiga, Ethiopia, North East Africa, Ethiopia. *E-Mail: krishnanaik.ece@gmail.com,*

[4]Assoc.Professor, Department of Electronics & Communications Engineering, Joginpally B.R Engineering college, Hyderabad, Andrapradesh, India. *E-Mail: rajua1999@gmail.com,*

Abstract: ***Images have large data capacity. For storage and transmission of images, high efficiency image compression methods are under wide attention. In this paper we implemented a wavelet transform, DPCM and neural network model for image compression which combines the advantage of wavelet transform and neural network. Images are decomposed using Haar wavelet filters into a set of sub bands with different resolution corresponding to different frequency bands. Scalar quantization and Huffman coding schemes are used for different sub bands based on their statistical properties. The coefficients in low frequency band are compressed by Differential Pulse Code Modulation (DPCM) and the coefficients in higher frequency bands are compressed using neural network. Using this scheme we can achieve satisfactory reconstructed images with increased bit rate, large compression ratios and PSNR.***

Keywords: Efficiency, subband, Huffman coding, DPCM, PSNR, Haar wavelets

1. INTRODUTION

Image compression is a key technology in the development of various multi-media computer services and telecommunication applications such as video conferencing, interactive education and numerous other areas. Image compression techniques aim at removing (or minimizing) redundancy in data, yet maintains acceptable image reconstruction. A series of standards including JPEG, MPEG and H.261 for image and video compression have been completed. At present, the main core of image compression technology consists of three important processing stages: pixel transforms, vector quantization and entropy coding. The design of pixel transforms is to convert the input image into another space where image can be represented by uncorrelated coefficients or frequency bands. Therefore, only those main frequency bands or principal components are further processed achieve image compression such as DCT, wavelets, etc. Vector quantization rounds up the values of transformed coefficients into clusters where points within a cluster are closer to each other than to vectors belonging to different clusters. Entropy coding is a form of lossless data compression in which statistical information of input data considered to reduce the redundancy. Typical algorithms are arithmetic coding, Huffman coding and run-length coding etc.

The use of sub band decomposition in data compression and coding has a long history. Sub band coding was first proposed by Crochiereet al. for medium bandwidth waveform coding of speech signals. This method decomposed the signal into different frequency bands using a bank of quadrature mirror filters(QMF's). Each sub band was subsequently encoded using differential pulse code modulation(DPCM). A varying bit assignment strategy was also used to allocate the bit rate for each sub band according to its statistical properties. Woods and O'Neil extended sub band decomposition to two-dimensional (2-D) signals and proposed a method for QMF design that eliminates possible aliasing error due to non ideal sub band filters. Recent advances in signal processing tools such as wavelets opened up a new horizon in sub band image coding. Studies in wavelets showed that the wavelet transform exhibits the orientation and frequency selectivity of images.

Neural networks approaches used for data processing seem to be very efficient, this is mainly due to their structures which offers parallel processing of data and, training process makes the network suitable for various kind of data. Sonhera et al have used a two layered neural network with the number of units in the input and output layers the same, and the number of hidden units smaller. The network is trained to perform the identity mapping and the compressed image is the output of the hidden layer. Arozullah et al presented a hierarchical neural network for image compression where the image is compressed in the first step with a given compression ratio; then the compressed image is itself compressed using another neural network. Hussan et al proposed a dynamically constructed neural architecture for multistage image compression [11]. In this architecture the necessary number of hidden layers and the number of units in each hidden layer are determined automatically for a given image compression quality. Gersho et al have used Kohonen Self-organizing Features Map (SOFM) for designing a codebook for vector quantization of images

Objective : To find the high compression ratio, Peak Signal to Noise ratio (PSNR) with increased bit rate by implementing the Discrete Wavelet Transform (DWT), DPCM and Neural Network.

2. Image Compression Models

The three general techniques for image compression are combined to form a practical image compression system. In the figure 1 shows the general compression system model consist of encoder path f(x, y) is the input image which is fed to the source encoder which creates set symbols of input data, these input data is transformed over the channel. The decoder receives the data through the channel and $\hat{f}(x,y)$ reconstructed from decoder. If $\hat{f}(x,y)$ is equal to input image then it is error free if not it is lossyimage (distorted image). Both encoder and decoder consist of sub block. The encoder consist source encoder which reduces the redundancy and channel encoder which increases the immunity of the source encoders output. The decoder part consists of channel decoder and source decoder. If the output image is noise free the channel encoder and source decoder is eliminated and general encoder and decoder becomes source encoder and decoder respectively.

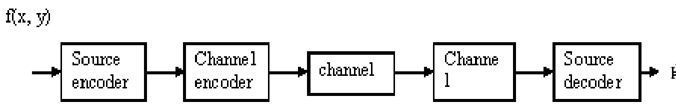

Figure 1: Image compression model

2.1 Image Compression Types : There are two types' image compression techniques

a) Error free compression: Error free compression strategies are providing 2 to 10 compression ratio. These compression strategies are applicable to both binary and gray level images. Error free compression is achieved using two techniques; 1) interpixel redundancy and 2) coding redundancy

b) Lossy Image compression: Lossy compression provides higher levels of data reduction but result in a less than perfect reproduction of the original image. It provides high compression ratio. Lossy image compression is useful in applications such as broadcast television, videoconferencing, and facsimile transmission, in which a certain amount of error is an acceptable trade-off for increased compression performance.

3.Basics of Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

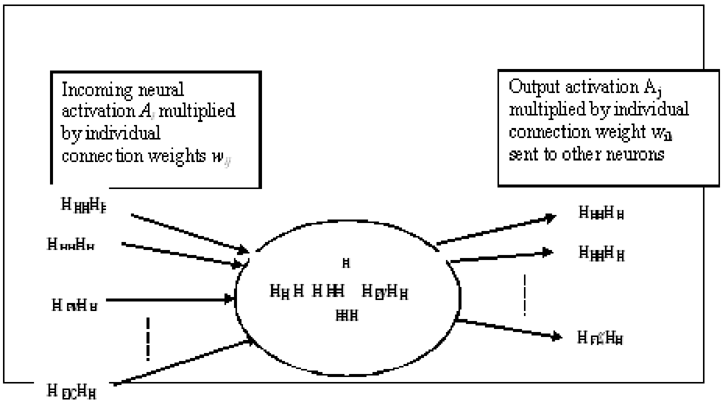

Figure2 : Three layered neural network.

4. Differential Pulse code Modulation (DPCM)

In typical DPCM system there are mainly two sub systems: encoder present in transmitter and decoder present in receiver side as shown in the figure 3, prediction and quantizer present in transmitter side and quantizer is eliminated in decoder part of receiver side, hence it is called lossy compression. Gray levels of adjacent pixels are highly correlated for most of images. Thus the autocorrelation function for the picture is used as a measure for coding. If f_{n-1} is having a certain gray level then the adjacent pixel f_n along the scan line is likely to have a similar values, where n is the number of pixels in the input image. The pixel gray levels in whole range of 256 values in an image have adjacent pixel difference that is very small in the range 20 gray level values.

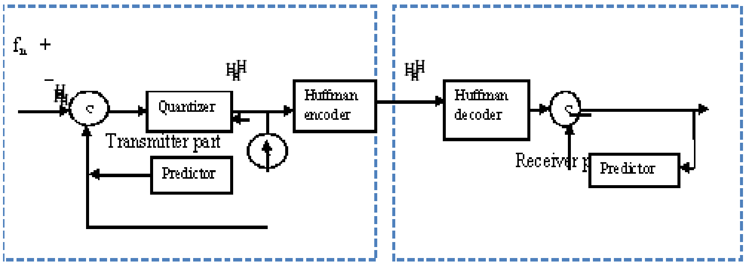

Figure 3: Block diagram of DPCM

DPCM make use of this property as follows: we conceder a pixel f_{n-1} and based on this observed values, we predict value of the next pixel f_n. Let $\hat{f}_n$ be the predicted value of f_n and let us suptract this from actual value $f_n$to get difference (e_n). The difference (e_n) will not the average be significantly smaller in magnitude then the actual magnitude of pixel f_n. Consequently we require fewer quantization levels and thus bits to code the sequence of differences then would be required to code the sequence of pixels.

4.1Predictor : In practical DPCM system, the current pixel value is first predicted from the previous pixel values. The difference between the current pixel and its predicted value is then quantized, coded, and transmitted to the receiver, which is in the decoder side (see figure 3). Prediction of current pixel $\hat{f}_n$

is denoted as $\hat{f}_n$ which is linear combination of n previous pixelsf_{n-1}, we define $\hat{f}_n$ as

$$\hat{f}_n = \sum_{j=1}^{m} \alpha_j f_{n-j} \quad \text{………} (1)$$

Where m is the order of the linear predictor and α_j for j=1, 2, 3…m are the prediction coefficient. The predictor error (e_n) is defined as the difference between input pixel f_n and predictor value ($\hat{f}_n$).

$$e_n = f_n - \hat{f}_n \quad \text{……………} (2)$$

The design of optimal prediction refers to the determination of prediction coefficient of order 1 it determine by using Levinson-Darbin algorithm some of the calculation is given of prediction error is in table (1).

Example: Let input pixels bef_n, with a predictor coefficient ($\alpha_j = 0.9838$, j=1) so we can find the predictor values ($\hat{f}_n$). The values of f_n and $\hat{f}_n$ are given in table 1.

Table 1 values of Predictor and error

N	f_n	$\hat{f}_n$	e_n
0	0	0	0
1	628.5	0	0
2	624.75	618.3183	6.4040
3	621.25	614.6290	6.5934
4	625.00	611.1875	13.7869
5	615.75	605.7748	0.8475
6	621.5	611.4317	9.1980
. . .			
10	627.00	616.8426	16.4357
11	626.5	616.3507	15.5409
. .			

4.2 Vector Quantization : Vector quantization is systems for mapping a sequence of discrete vectors into digital sequence, suitable for communication or shortage in a digital channel. The function of such system is data compression, to reduce the bit rat while maintaining the fidelity of data compression is to obtain the best possible fidelity for given rate. An N-level quantizer will be said to be optimal (or globally optimal) if it minimizes the expected distortion, that is, q***** is optimal if for all other quantizers***q*** having ***N*** reproduction vectors ***D(q*)*** <***D(q),*** in this project we are using 8-level quantizer**. A** quantizer is said to belocally optimum if ***D(q)*** is only a local minimum, that is, slight changes in *q* cause an increase in distortion. The goal of block quantizer design is to obtain an optimal quantizer if distortion is grater then10^{-7} and, if not, to obtain a locally optimal and hopefully “good” quantizer. .Several such algorithms have been proposed in the literature for the computer-aided design of locally optimal quantizers. In a few special cases, it has been possible to demonstrate global optimality either analytically or by exhausting all local optima. In 1957,in a classic but unfortunately unpublished Bell Laboratories’ paper, S. Lloyd proposed two methods for quantizer design for the scalar case ***(k*** = 1) with a squared error distortion criterion. His “Method **II”** was a straightforward varitional approach wherein he took derivatives with respect to the reproduction symbols, y_i, and with respect to the boundary points defining the ***Si*** and set these derivatives to zero. This in general yields only a “stationary point” quantizer (a multidimensional zero derivative) that satisfies necessary but not sufficient conditions for optimality. By second derivative arguments, however, it is easy to establish that such stationary-point quantizers are at least locally optimum for v^{th}-power law distortion measures. In addition, Lloyd also demonstrated global optimality for certain distributions by a technique of exhaustively searching all local optima. Essentially the same technique was also proposed and used in the parallel problem of cluster analysis by Dalenius in 1950, Fisher in 1953, and Cox in 1957. The technique was also independently developed by Max in 1960 and the resulting quantizer is commonly known as the Lloyd-Max quantizer. Lloyd-Max algorithm is used to design good quantizer.

Lloyd- Max Algorithm

Step 1: Create a 20 initial code book values (-1 to +1) with an increment of 0.1.

Step 2: find partition (P)

$$P = \sum_{i=2}^{21} \sum_{j=1}^{20} \mathrm{codebook(i)} + \mathrm{code\ book(j)}/2 \quad \text{………} (3)$$

With respect to these partition values we are assigning or separating the error values. If the first pixel of e_n is grater then +0.95 then it is given as 20 or it is grater then0.85and less than 0.95 then it is given as 19.

Step 3: find the distortion (D)

Initial distortion = 0

$$D(i+1) = \sum_{i=0}^{20} (D(i) + \mathrm{index} - \mathrm{codebook}(i+1).\hat{}2) \text{ ….} \quad (4)$$

Step 5: D= D/length of prediction error

The quantize value we have to use partition error and group the same partition value and then find mean value is the new partition.

Out put of the quantizer we get only 1 to 20 decimal numbers of the error values (e_n) of low frequency image of size 64X64. The error image or compressed image of DPCM is shown in fig (3).

4.3 High Frequency Band Compression with Neural Network : Artificial Neural Network have been applied to high frequency image compression but not low frequency images because the inter pixel relationship of an image is highly nonlinear and unpredictive in the absence of prior knowledge of the image itself. So predictive approaches would not work well with neural images. The architecture of the Neural Network for high frequency band compression is as shown in fig. The input data which consist of nx1 vector is band -2 to -4of size 64X64 and band -5 to -7 of size 128X128 is applied to the input layer. The data at the input layer is then transformed by neural network to hidden layer. The input vector is now represented by a kx1 vector at the hidden layer, which is quantized and then transmitted or stored, depending on application. Typically number of neurons present at the hidden layer is less then input layer and output layer. The number of neurons present at the input layer is equal to number of neurons present at output layer. At the output layer (receiver part), the kx1 vector is transformed to output layer, the output vector is the nx1 vector at the output layer.

The operation of the neural network is explained with fig (4). The three layered neural network systems assumes no quantization error and per transmission of the hidden layer values. The i^{th} input vector x denoted as x_i is simply the value at the i^{th} node of the input layer. In similar manner, the kx1 hidden vector h is formed from k values at the output nodes and is formed from the n values at the output nodes.The every node of the input layer is connected to the each and every node of the hidden layer. The weight w_{ij} is chosen between x_i input layer to h_j hidden layer. Then the k element of hidden vector h are related to n elements of input vector x by expression

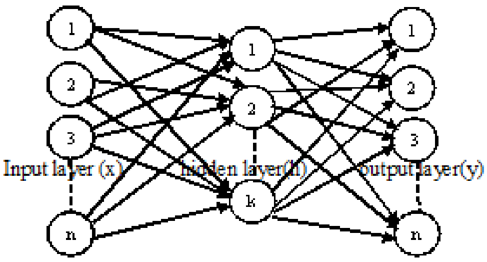

Figure4: Three Layered Neural Network

$$h_j = \sum_{i=1}^{n} w_{ij}\, x_i \quad , \ \dots\dots\dots\dots\dots\dots\ (5)$$

Where j=1, 2, 3…….k.

Similarly the weight between hidden layer and output layer is chosen i.e. the weight between the h_j and y_i is w_{ij}, then the n elements of output layer are related to k elements of hidden layer by the expression.

$$y_i = \sum_{j=1}^{k} w_{ij}\, h_j \quad , \ \dots\dots\dots\dots\dots\dots\ (6)$$

Where i=1, 2, 3…….n.

Equation (5) and (6) can be simplified if we form a matrix W which has weight w_{ij} as element (i, j) of the matrix equation (5) and (6) can be then rewritten as

$$h = W^T x, \quad \dots\dots\dots\dots\dots\dots\ (7)$$

and $y = Wh = WW^T x$, ………………...….. (8)

If the weight matrix W is written in terms of k vectors of dimention nx1which makes up columns of W, i.e.,

$$W=[w_1,w_2,w_3, \dots\dots,w_k] \ , \ \dots\dots\dots\dots\dots\ (8)$$

Then the output vector y can be written as

$$y = \sum_{j=1}^{k} (W_j^T x)\, W_j, \quad \dots\dots\dots\dots\dots\dots\ (9)$$

this shows that the Neural Network projects input vector onto the k-dimensional space spanned by the columns of weight matrix W. the element h_j of hidden vector h is the coefficient that the j^{th} column of W must be multiplied by to get projection of input vector x onto the j^{th} column W. The sum of these individual projections is projection of input vector on to the space spanned by the columns of the weight matrix.

4.5 Training the Neural Network for Compression : The Neural Network is used to compress the high frequency data if the connection weights are chosen properly. The weight should be chosen to minimize the distortion between the input vectors and output vectors for a given error criteria.Back propagation algorithm is used to minimize mean square error (MSE) between the input vector and output vector for the training set.

4.5.1Backpropogationalgorithm : Back-propagation algorithm is a widely used learning algorithm in Artificial Neural Networks. The Feed-Forward Neural Network architecture is capable of approximating most problems with high accuracy and generalization ability. This algorithm is based on the error correction learning rule. Error propagation consists of two passes through the different layers of the network, a forward pass and a backward pass. In the forward pass the input vector is applied to the sensory nodes of the network and its effect propagates through the network layer by layer. Finally a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weight of the networks are all fixed. During the back pass the synaptic weights are all adjusted in accordance with an error-correction rule. The actual response of the network is subtracted from the desired response to produce an error signal. This error signal is then propagated backward through the network against the direction of synaptic conditions. The synaptic weights are adjusted to make the actual response of the network move closer to the desired response.

Step 1: Normalize the inputs and outputs with respect to their maximum values. It is proved that the neural networks work better if input and outputs lie between 0-1. For each training pair, assume there are ‘n’ inputs given by $\{x_i\}$ of size nx1 and ‘n’ out puts $\{y_i\}$ of size nx1 in a normalized form.

Step2: Assume the number of neurons in the hidden layer to lie between l<j<k

Step3: [v] represents the weights of synapses connecting Input neurons and hidden neurons and [w] represents weights of synapses connecting hidden neurons and output neurons. Initialize the weights to small random values usually from -1 to 1.For general problems, λ can be assumed as 1 and the threshold values can be taken as zero.

[v] = [random weights] $[w_{ij}]$ = [random weights] [Δv] = [Δw] = [O]

Step4: For the training data, present one set of inputs and outputs. Present the pattern to the input layer as inputs to the input layer. By using linear activation function, the output of the input layer may be evaluated as

$$\{O\}_r = \{r\}_r \quad \dots\dots\dots\dots\dots\dots\dots\dots\ (9)$$

The size of $\{o\}_r$ and $\{r\}_r$ is 1x1

Step 5: Compute the inputs to the hidden layer by multiplying corresponding weights of synapses as

$$\{x\}_H = [V]^T \{O\}_r \quad \dots\dots\dots\dots\dots\dots\dots\dots\ (10)$$

The matrix size of $\{x\}_H$,$[V]^T$ and $\{O\}_r$ is nx1,nx1 and 1x1

Step6: Let the hidden layer units evaluate the output using the sigmodial function as

$$\{O\}_h = \left\{ \begin{matrix} \vdots \\ \frac{1}{(1+e^{-x_{h_i}})} \\ \vdots \end{matrix} \right\}_{mx1} \quad \dots\dots\dots\dots\dots\dots\ (11)$$

Step7: Compute the inputs to the output layer by multiplying corresponding weights of synapses as

$$\{x_i\} = [W]^T\{O\}_h \qquad \text{(12)}$$

The matrix size of x_i is n x 1, W^T is n x m, and O_h is m x 1

Step8: Let the output layer units evaluate the output using sigmoidal function as

$$\{O\}_y = \left\{ \begin{matrix} \vdots \\ \frac{1}{(1+e^{-x_{y_i}})} \\ \vdots \end{matrix} \right\} \qquad \text{(13)}$$

The above is the network output.

Step9: Calculate the error and the difference between the network output and the desired output as for the i^th training set as

$$E^p = \frac{\sqrt{(T_i - y_{oi})^2}}{n} \qquad \text{(14)}$$

Step10: Find {d} as

$$\{d\} = \left\{ \begin{matrix} \vdots \\ (T_h - y_{oi}) y_{oi} (1 - y_{oi}) \\ \vdots \end{matrix} \right\} \qquad \text{(15)}$$

Step 11: Find [Y] matrix of mxn size as

$$[Y] = \{O\}_y \langle d \rangle \qquad \text{(16)}$$

Step 12: Find

$$[\Delta w]^{t+1} = \alpha\, [\Delta w]^t + \eta [Y] \qquad \text{(17)}$$

Δw is of size m x n

Step 13: Find

$$\{e\} = [w]\{d\} \qquad \text{(18)}$$

$$\{d^*\} = \left\{ \begin{matrix} \vdots \\ e_i (O_y)(1 - O_y) \\ \vdots \\ \vdots \end{matrix} \right\}_{nx1} \qquad \text{(19)}$$

Find [X] matrix as

$$\underset{1\,x\,m}{[X]} = \underset{1\,x\,1}{\{O\}\,I}\ \underset{1\,x\,m}{\langle d^* \rangle} = \underset{1\,x\,1}{\{I\}I}\ \underset{1\,x\,m}{\langle d^* \rangle} \qquad \text{(20)}$$

Step 14: Find

$$[\Delta v]^{t+1} = \alpha\, [\Delta v]^t + \eta [X] \qquad \text{(21)}$$

Step 15: Find

$$[v]^{t+1} = [v]^t + [\Delta v]^{t+1} \qquad \text{(22)}$$

$$[w]^{t+1} = [w]^t + [\Delta w]^{t+1} \qquad \text{(23)}$$

Step 16: Find error rate as

$$\text{Error rate} = \frac{\sum E^p}{nset} \qquad \text{(24)}$$

Step 17: Repeat steps 4 -16 unit the convergence in the error rate is less than the tolerance value.

4.5.2 Huffman Encoder : The well known technique for removing the coding redundancy is due to the Huffman (Huffman [1952]). When coding the symbols of an information source i.e. quantized output of DPCM and neural network individually, Huffman coding the smallest possible number of code symbols per source symbols. In terms of noise less coding theorem (Refer section8.3 of Rafael C. Gonzalez and Richard E. woods) the resulting code is optimal for a fixed value of n subject to the constraint that the source symbols be coded one at a time.The process of Huffman encoder is explained in step by step.The original source symbols with probability ($P_r(r_k)$) is given in the Table 1

Step1: Probabilities of source symbol are arranged in descending order, i.e. top to bottom of the look up table (see Table2).

Step2: Adding up the two lowest probability symbols from bottom to top to a single symbol and replace them in next column of source reduction of figure (4.)

Step3: Repeat step1 and step2 until the two probability symbols are obtained.

symbols	Probability($P_r(r_k)$)
X8	0.0001
X9	0.0065
X10	0.0225
X11	0.0192
X12	0.0179
X13	0.0222
X14	0.0233
X15	0.0257

Table 2 Huffman lookup table for Original source

Original source				Source reduction				
Sym.	$P_r(r_k)$	code	1	2	3	4	5	6
X15	0.0257	01	0.0257, 01	0.0257, 01	0.0414, 01	0.0458, 00	0.0502, 1	0.0872, 0
X24	0.0233	000	0.0233, 000	0.0245, 11	0.0257, 01	0.0414, 01	0.0458, 00	0.0502, 1
X10	0.0225	001	0.0225, 001	0.0233, 000	0.0245, 11	0.0257, 10	0.0414, 01	
X13	0.0222	010	0.0222, 010	0.0225, 001	0.0233, 000	0.0245, 11		
X11	0.0192	011	0.0192, 011	0.0222, 010	0.0225, 001			
X12	0.0179	110	0.0179, 110	0.0192, 011				
X9	0.0065	1110	0.0066, 111					
X8	0.0001	1111						

Table 3 Huffman code assigning procedure

The second step in the Huffman coding is to code each reduced source starting with a smallest source and working back to the original source. Fig (4.) shows the procedure of assigning two binary symbols 0 and 1 in reverse order. From right to left as the reduced source symbol with probability 0.6 was generated by combining two symbols in the reduced source to its left, the 0 used to code it is now assigned to both symbols, and a 0 and 1 are arbitrarily appended to each to distinguish them from each other. This process is then repeated for each reduced source until the original source is reached. The finalized code appears at the far left in fig (2). The average length of this code is

L_{avg} = (0.0257)(2) + (0.0233)(3) +(0.0225)(3) + (0.0222)(3) + (0.0192)(3) + (0.0179)(3) + (0.0065)(4) + (0.0001)(4)

=0.3931 bits/symbols

Finally we required 0.3931 bits/symbols to code the information source.The Huffman's procedure creates the optimal code for asset of symbols and probabilities subjects to the constraint that the symbols be coded, coding and /or decoding is accomplished in a simple look up table manner.

5. Complete Image Compression &Decompression for Input Image

The accuracy of decompressed image is less when compare to input image hence it is known as a lossy compression.

5.1 Complete Image Compression Scheme : Fig (5) shows the block diagram of complete image compression system. First the image is decomposed into different frequency bands these frequency bands are low frequency band and high frequency bands the lowest frequency band represents the one forth of original resolution, is coded using DPCM. The remaining frequency bands are coded using neural network compression scheme.The low frequency band-1 is compressed with Optimal DPCM which reduces the inter pixel redundancy. Depending upon previous pixel information we can predict the next pixel, the difference between current pixel and predicted pixel is given to optimal quantizer which reduces the granular noise and slop over lode noise.Finally we get the error output from DPCM the corresponding image is shown in fig (5.3), these error values are scalar quantized.The Human Visual System (HVS) has different sensitivity to different frequency components, for this reason we are going for neural network, neural networks of different sizes must be used to allow for different reconstruction quality, resulting in different compression ratios for the various frequency bands. Band-2 and band-3 is coded using identical three layer neural network.

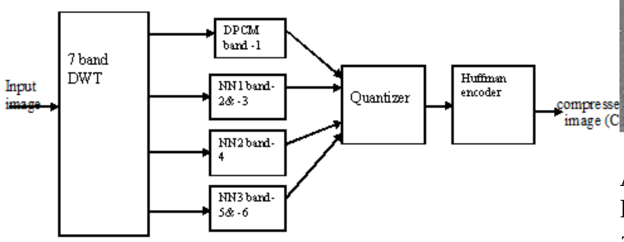

Figure 5.1: Block diagram of implementation of wavelet transform, DPCM, neural network for image compression.

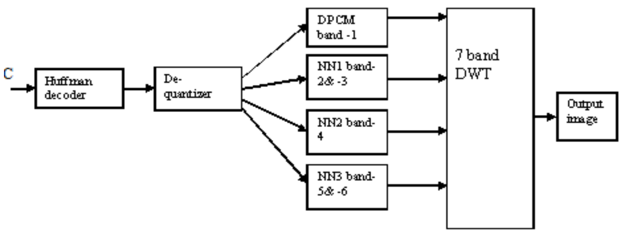

Figure 5.2: Block diagram of decompression

Figure (3.4) shows that band-2 and-3 contains the same frequency content for different orientation, band-2 contains low frequency in x-direction and high frequency in y-direction, while the band-3 contains low frequency in y-direction and high frequency in x-direction. This means that the band-2 contains vertical edge information the respected image is shown in figure (5.4) and band-3 contains the similar edge information in the horizontal direction which is shown in figure (5.5) as a result 64x1 vectors from band -2 are quite similar to 1x64 vectors from band-3, which allows us to use a single neural network to compress these two bands. Using similar reasoning we use the same neural network to compress the data in band-5 and band-6 the compressed image of band -5 and band -6 are shown in the figure (5.7) and figure (5.8). The information in band-7 is discarded. This frequency band contributes little to the image from the stand point of the HVS, the image of band-7 is shown in fig (5.9), so the coefficients in this band can be assumed to be zero with little effect on the quality of the reconstructed image. The information in band -4 does not have a considerable effect on reconstructed image, and since there is no other band with similar frequency characteristics, band-4 is coded using a separate neural network the compressed image of band-4 is shown in figure (5.6).

Figure5.3 Image of band-1

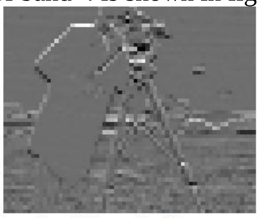

Figure5.3 Image of band-2

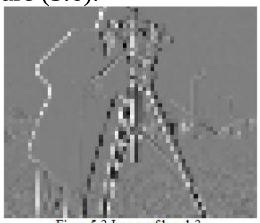

Figure5.3 Image of band-3

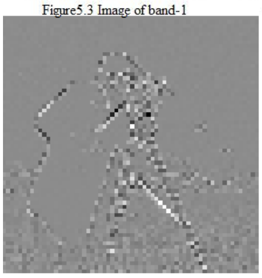

Figure5.3 Image of band-4

Figure5.3 Image of band-5

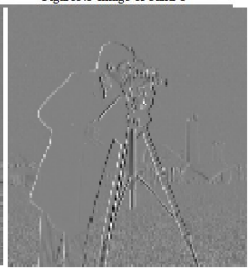

Figure5.3 Image of band-6

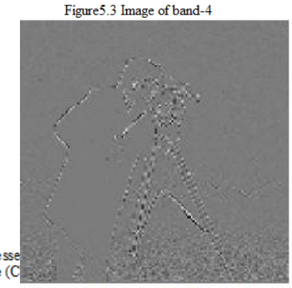

Figure 5.3 Image of band-7

After the wavelet coefficient are compressed using either DPCM or by using neural network. The output of the DPCM and neural network are scalar quantized where the values of entire kx1 hidden vectors are scalar quantized at once. The results are given in the next section. Finally, the quantized values are Huffman encoded.

5.2 Decompression scheme : The block diagram of decompression scheme for compressed image (compressed bit stream) is shown in figure 5.2. The output of the Huffman encoder is given to Huffman decoder, these reconstructed bit streams are dequantized, the output of the dequantized values are frequency band-1 to band-7, band-1 is compressed low frequency band and ban-2 to band-7 are compressed high frequency bands. The compressed low frequency components are given to inverse DPCM (IDPCM) in inverse DPCM quantization will not be present. The compressed frequency bands are given to output layer of the neural network, and then we get reconstructed sub bands. These reconstructed sub bands are given to Inverse Discrete Wavelet Transform (IDWT), the output of the IDWT is our desire output i.e. reconstructed image (see figure5.10).

6.Results&Discussion:

Input image (cameraman image) of size 256 X 256 is decomposed into seven frequency bands with different resolutions is compressed with DPCM, and neural network, these compressed image is scalar quantized and the quantized bits ire Huffman encoded.

6.1 Results of implementation of DWT, DPCM and neural network for image compression : The experiment evaluates the effect of discreet Haar wavelet filters on the quality of the reconstructed image. In the experiment where conducted using cameramen image of size 256 X256with 2^8=256 gray levels. The image was decomposed using Haar wavelet transform. Coefficients of bant-1 see above figure is coded with differential pulse code modulation (DPCM), coefficients of band -2 and band -3 are coded using neural network which has eight input units and eight output units, and six hidden units, i.e., a 8 - 6 - 8 neural network. To compresses the coefficients of band-4 we use an eight input units and eight output units and four hidden units i.e., 8 - 4 - 8 neural network and band 5 and 6 uses sixteen input units and sixteen output units, and one hidden unit i.e., 16 – 1 – 16 neural network these compressed information is scalar quantizer and the coefficients of hidden layer is encoded with Huffman encoder the compressed image and original image is shown in figure 6.1. The results was evaluated by PSNR and compression ratio (CR) defined for the image of size M X M as

$$\text{PSNR} = 10\log_{10}\frac{255^2}{\frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}(I_{ij}-\hat{I}_{ij})^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 2.1$$

$$\text{CR} = \frac{\text{input image size}}{\text{output image size}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ 2.2$$

Where 255 is peak signal value, I_{ij} and $\hat{I}_{ij}$ are the input image pixel and output image pixels respectively. The results of implementation of wavelet transform, DPCM and neural network is given in table 4.The input and reconstructed figures are shown in figure6.1 and figure 6.2



Figure 6.1 Cameraman input mage Figure6.2 reconstructed image 6.3 (a) compressed of DPCM.

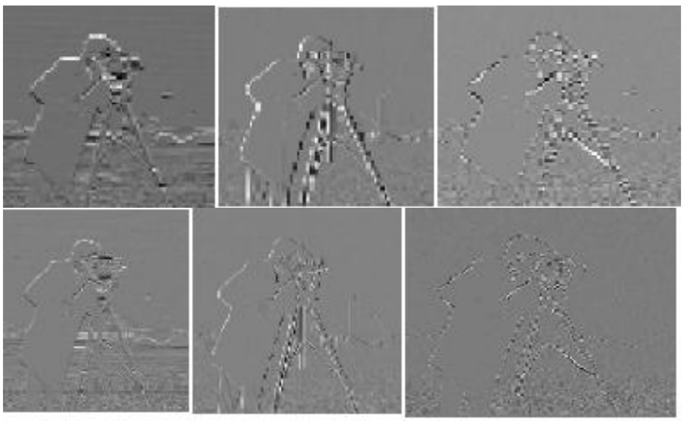

Figure 6.3 (b) – (g) Compressed image of band -2 to -7 of neural network

Table 4: Compression ratio, PSNR and bit rate for implementation of DWT, DPCM and neural network for cameramen image

	Compression ratio	PSNR	Bit rate
Discreet Haar wavelet transform	12.1726:1	32.4762db	0.6666 Bits/pixel

7.CONCLUSION : In this thesis we presented a implementation of wavelet transform, DPCM and Neural Network for image compression method. Compared to the neural network applied on the original image wavelet based decomposition improved dramatically the quality of reconstructed images. Wavelet decomposition eliminates blocking effects associated with DCT. Haar wavelet resulted slightly better reconstructed image with a 32.4762db PSNR, compression ratio 12.1726:1 and with an increased bit rate of 0.6666bits/pixel when compare with Daubechiesfilteres which is used in Neuro wavelet based approach for image compression paper.

REFERENCE

[1] P. C. Millar, , "Recursive quadrature mirror filters—Criteria specification and design method," IEEE Trans. Acoust., Speech, Signal Processing, vol. 33, 1985, pp. 413–420.

[2] M. H. Hassan, H. NaitCharif and T. Yahagi, , "A Dynamically Constructive Neural Architecture for Multistage Image Compression", Znt. Conference on ~ Circuits, Systems and Computer,(IMACS-CS'98). 1998.

[3] Ronald E.Crochiere and Lawrence R. Rabiner, multirate digital signal processing Printi- Hall, Englewood Cliffs, NJ, 1983.

[4] S. G. Mallat, , "Multi frequency channel decomposition of images and wavelet models," IEEE Trans. Acoust., Speech, Signal Processing, vol. 37, 1989, pp. 2091–2110.

[5] J. W. Woods and S. D. O'Neil, , "Sub band coding of images," IEEE Trans. Acoust., Speech, Signal Processing, vol. 34, 1986, pp. 1278–1288.

[6] B. Ramamurthi, A. Gersho. "Classified Vector Quantization of Images" IEEE Transactions on Communications, Vol.Com-34, No. 11, 1986,

[7] M. Mougeot, R. Azeneott, B. Angeniol, "Image compression with back propagation: improvement of the visual

restoration using different cost functions" neural networks,vol 4, No 4 1991, pp 467-476
[8] M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies, "Image coding using wavelet transform," IEEE Trans. Image Processing, vol. 1, 1992, pp. 205–220.
[9] D. Esteban and C. Galand, "Applications of quadrature mirror filters to split band voice coding schemes," in Proc. IEEE Int. Conf. Acoustics, Acoustics, Speech and Signal Processing, Washington, DC, 1979, pp. 191–195.
[10] Manphol s. Chin and M. Arozullah, ''Image compression with a hierarchical neural networks", IEEE Trans. Aerospace and Electronic Systems, vol. 32, no 1. 1996,
[11] S. G. Mallat, ,"A theory for multi resolution signal decomposition: The wavelet representation," IEEE Trans. Pattern Anal. Machine Intell., vol. 11, 1989, pp. 674–693.

Sri.V.KRISHNANAIK, pursuing Ph.D., currently working as Asst. Professor, in the **Department of Electrical & Computer Engineering**, **College of Engineering & Tech,Aksum University**, Axum, Ethiopia and North East Africa.He studied **B.E (ECE)** from **C.B.I.T, Osmania University**, Hyderabad and **M.Tech(Systems & Signal Processing)** from **J.N.U.C, J.N.T.U,** Hyderabad, A.P, India. He is having 12+ years of work experience in **Academics, Teaching, and Industry & Research**. He participated and presented research papers in both national and international conferences, seminars and workshops; also published 7 research papers in national and international peer reviewed journals.

Dr.G.Manoj Someswar, B.Tech., M.S.(USA), M.C.A., Ph.D. is having 20+ years of relevant work experience in Academics, Teaching, Industry, Research and Software Development. At present, he is working as PRINCIPAL and Professor CSE Department Anwarul-uloom College of Engineering & Technology, Yennepally, Vikarabad - 501101, RR Dist., A.P., and utilizing his teaching skills, knowledge, experience and talent to achieve the goals and objectives of the Engineering College in the fullest perspective. He has attended more than 100 national and international conferences, seminars and workshops. He has more than 10 publications to his credit both in national and international journals. He is also having to his credit more than 50 research articles and paper presentations which are accepted in national and international conference proceedings both in India and Abroad. He received National Awards like Rajiv Gandhi Vidya Gold Medal Award for Excellence in the field of Education and Rashtriya Vidya Gaurav Gold Medal Award for Remarkable Achievements in the field of Education.

Mr.K.Purushotham, M.Tech. is having 8+ years of relevant work experience in **Academics, Teaching, Industry and Research**. He participated and presented research papers in both national and international conferences, seminars and workshops; also published 3 research papers. At present, he is working as **Senior Lecturer in the Department of Electrical & Computer Engineering, Jigjiga University,** Jigjiga, Ethiopia, North East Africa. He studied **B.Tech (EC**E) from **GRRIET,** JNTU Hyderabad and **M.Tech (Systems and Signal Processing)** from **JNTUCEH**, Hyderabad, A.P, India.

Sri.A,RAJAIAH, pursuing Ph.D.from JNTU UNIVERSITY,currently working as an Associate Professor, in the **Department of Electronics and communication Engineering, Joginpally B.R Engineering college,Moinabad, Rangareddy Dist, Hyderabad, Andrapradesh, India**.He studied **B.E (ECE)** from **C.B.I.T, Osmania University**, Hyderabad and **M.Tech(Systems & Signal Processing)** from**, J.N.T.U,** Hyderabad, A.P, India. He is having 12+ years of work experience in **Academics, Teaching, and Industry & Research**. He participated and presented research papers in both national and international conferences, seminars and workshops; also published 1 research paper in international peer reviewed journal.