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Abstract— **The rapid growth of digital imaging applications, including desktop publishing, multimedia, teleconferencing, and high definition television (HDTV) has increased the need for effective and standardized image compression techniques. Among the emerging standards are JPEG, for compression of still images; MPEG, for compression of motion video; and CCITT H.261 (also known as Px64), for compression of video telephony and teleconferencing. All three of these standards employ a basic technique known as the discrete cosine transform (DCT), Developed by Ahmed, Natarajan, and Rao [1974]. Image compression using Discrete Cosine Transform (DCT) is one of the simplest commonly used compression methods. The quality of compressed images, however, is marginally reduced at higher compression ratios due to the lossy nature of DCT compression, thus, the need for finding an optimum DCT compression ratio. An ideal image compression system must yield high quality compressed images with good compression ratio, while maintaining minimum time cost. The neural network associates the image intensity with its compression ratios in search for an optimum ratio.**

Keywords— **Image Compression, Discrete Cosine Transform, Neural Networks, Optimum Compression.**

1. INTRODUCTION

Data compression in multimedia applications has become more vital lately where compression methods are being rapidly developed to compress large data files such as images [1]. Efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size [2].

Recently the use of Wavelet Transforms and Discrete Cosine Transform (DCT) for image compression was investigated [3]. The usability and efficiency of these methods depend on the application areas that require either high transmission rate or high quality decompression. Lossless compression algorithm provides a compression which, when decompressed the exact original data can be obtained. This is the case when binary data such as executables and documents are compressed. On the other hand, images might not be reproduced 'exactly', but an approximation of the original image is enough for most purposes as long as the error between the original and the compressed image is tolerable. The general purpose of compression systems is to compress images, but the result is less than optimal. Image compression using DCT is a simple compression method that was first applied in 1974 [4]. It is a popular transform used for some of the image compression standards in lossy compression methods. The disadvantage of using DCT image compression is the high loss of quality in compressed images, which is more notable at higher compression ratios.

Instead of using the visual inspection and observation by humans which is an empirical analysis that involves a number of people who observe the smoothness and edge continuity of certain objects within reconstructed images and then decide which compression ratio provides a compromise between high compression ratio and minimal loss of quality [3], [5], the method to find out optimum compression ratio by using artificial neural network is suggested.

The aim of the work presented within this paper is to develop an intelligent optimum image compression system using DCT compression and a neural network. The novel method suggests that a trained neural network can learn the non-linear relationship between the intensity (pixel values) of an image and its optimum compression ratio.

This paper will give the theoretical review of DCT and the actual proposed work. The coding for DCT is done in C language and ANN part will be coded with MATLAB. The actual results will be compared with the results given in [3].

2. IMAGE DATABASE

The development and implementation of the proposed intelligent optimum image compression system uses 60 images from our database that have different objects, brightness and contrast. DCT compression has been applied to 50 images using 9 compression ratios (10%, 20%, 30%,… 90%) The optimum DCT compression ratios for the 50 images were determined using the optimum compression criteria based on visual inspection of the compressed images as suggested in [3], thus providing 50 images with *known* optimum compression ratios and 10 images with *unknown* optimum compression ratios. The image database is then organized into three sets:

• Training Image Set: contains 30 images with known optimum compression ratios which are used for the neural network within the intelligent system.

• Testing Image Set 1: contains 20 images with *known* optimum compression ratios which are used to test and evaluate the efficiency of the trained neural network.

Testing Image Set 2: contains 10 images with *unknown* optimum compression ratios which are used to further test the trained neural network within the intelligent system.
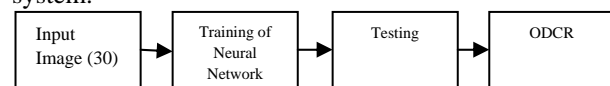
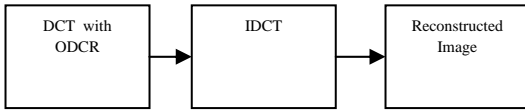Figure 1: Block Diagram of Optimum Image Compression System

Figure 2: DCT and IDCT to get the Original Image.

3. DISCRETE COSINE TRANSFORM

A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio and images (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as explained below, fewer are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers.

The DCT, and in particular the DCT-II, is often used in signal and image processing, especially for lossy data compression, because it has a strong "energy compaction" property (Rao and Yip, 1990): most of the signal information tends to be concentrated in a few low-frequency components of the DCT.

The DCT is used in JPEG image compression, MJPEG, MPEG, and DV compression. There, the two-dimensional DCT-II of N x N blocks are computed and the results are quantized and entropy coded. In this case, *N* is typically 8 and the DCT-II formula is applied to each row and column of the block. The result is an 8×8 transform coefficient array in which the (0,0) element (top-left) is the DC (zero-frequency) component and entries with increasing vertical and horizontal index values represent higher vertical and horizontal spatial frequencies.

The following is a general overview of the JPEG process.
- The image is broken into 8x8 blocks of pixels.
- Working from left to right, top to bottom, the DCT is applied to each block.
- Each block is compressed through quantization.
- The array of compressed blocks that constitute the image is stored in a drastically reduced amount of space.
- When desired, the image is reconstructed through decompression, a process that uses the Inverse Discrete Cosine Transform (IDCT).

The DCT equation:

The DCT equation computes the ith and j^{th} entry of the DCT of an image.

$$D(i,j) = \frac{1}{\sqrt{2N}} C(i)C(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} p(x,y) \cos\left[\frac{(2x+1)i\pi}{2N}\right] \cos\left[\frac{(2y+1)j\pi}{2N}\right]$$

$$C(u) = \frac{1}{\sqrt{2}} \quad \text{if } u=0,$$
$$= 1 \quad \text{if } u>0. \tag{Eq.1}$$

$p(x,y)$ is the xth and y^{th} element of the image represented by the matrix p. N is the size of the block that the DCT is done on. The equation calculates one entry (i,j^{th}) of the transformed image from the pixel values of the original image matrix. For the standard 8x8 block that JPEG compression uses, N equals 8 and x and y range from 0 to 7. Therefore D(i,j) would be as follows:

$$D(i,j) = \frac{1}{4} C(i)C(j) \sum_{x=0}^{7} \sum_{y=0}^{7} p(x,y) \cos\left[\frac{(2x+1)i\pi}{16}\right] \cos\left[\frac{(2y+1)j\pi}{16}\right]$$

$$\tag{Eq. 2}$$

Because the DCT uses cosine functions, the resulting matrix depends on the horizontal, diagonal, and vertical frequencies. Therefore an image black with a lot of change in frequency has a very random looking resulting matrix, while an image matrix of just one color, has a resulting matrix of a large value for the first element and zeros for the other elements.

Images with nine different compression ratios are shown in figure 3.

Figure 3: Images with nine different compression ratios

4. NEURAL NETWORK IMPLEMENTATION

The neural network will be trained with the coefficients of the DCT matrix. The intelligent optimum image compression system uses a supervised neural network based on the back propagation learning algorithm, due to its implementation simplicity, and the availability of sufficient "input / target" database for training this supervised learner. The hypothesis which is presented within this paper suggests that a trained neural network can learn the nonlinear

relationship between the image intensity (pixel values) and its optimum compression ratio. The neural network relates the image intensity (pixel values) to the image optimum compression ratio having been trained using images with predetermined optimum compression ratios. The ratios vary according to the variations in pixel values within the images. Once trained, the neural network would select the optimum compression ratio of an image upon presenting the image to the neural network by using its intensity values.

The images with predetermined optimum compression ratios are shown in figure 5.
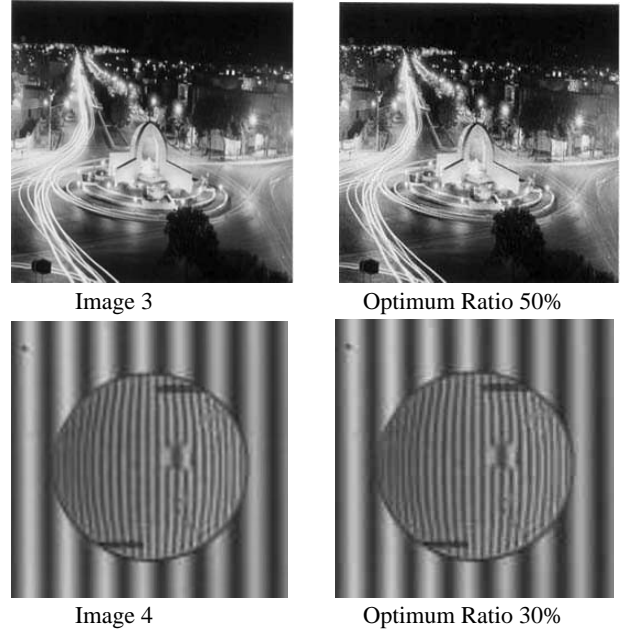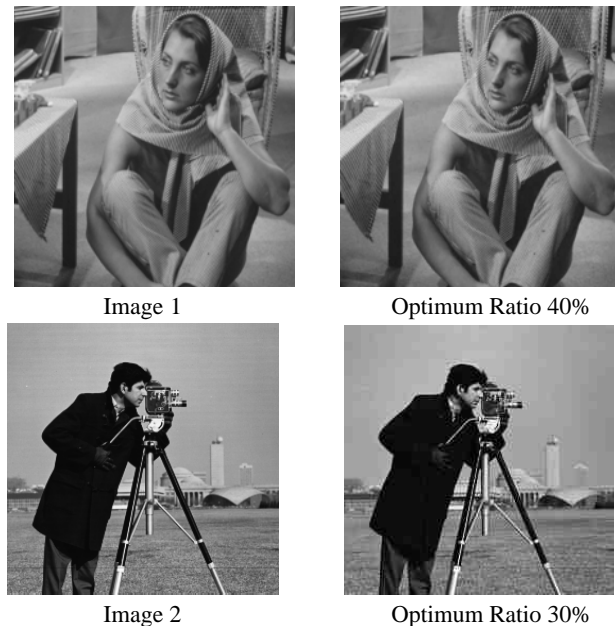

Figure 4: Training Image Database

| Image 1 | Optimum Ratio 40% |

| Image 2 | Optimum Ratio 30% |

| Image 3 | Optimum Ratio 50% |

| Image 4 | Optimum Ratio 30% |

Figure 5: Original Images and their optimum compression ratios

5. EVALUATION

Evaluation of Neural Network:

The evaluation of the training and testing results was performed using two measurements: the recognition rate and the accuracy rate. The recognition rate is defined as follows:

$$RR_{ODC} = \frac{I_{ODC}}{I_t} * 100 \quad \text{(Eq. 3)}$$

Where RR_{ODC} is the recognition rate for the neural network within the optimum DCT compression system, I_{ODC} is the number of optimally compressed images, and I_T is the total number of images in the database set.

The accuracy rate RA_{ODC} for the neural network output results is defined as follows

$$RA_{ODC} = \left(1 - \frac{mod(S_P - S_i * 10)}{S_t}\right) * 100 \quad \text{(Eq. 4)}$$

where S_P represents the pre-determined (expected) optimum compression ratio in percentage, S_i represents the optimum compression ratio as determined by the trained neural network in percentage and S_t represents the total number of compression ratios.

The Optimum Compression Deviation (OCD) is another term that is used in our evaluation. *OCD* is the difference between the pre-determined or expected optimum compression ratio S_P and the optimum compression ratio S_i as determined by the trained neural network, and is defined as follows:

$$OCD = mod\ (Sp - St) * 10 \qquad \text{(Eq. 5)}$$

The OCD is used to indicate the accuracy of the system, and depending on its value the recognition rates vary.

After getting the optimum compression ratio of a particular image, that image will be compressed with the DCT algorithm which will be coded in C language, for that particular compression ratio. The inverse DCT (IDCT) will be taken.

Evaluation of Compression Algorithm:

The performance measures of reconstructed image will be calculated such as PSNR which is a ratio of reconstructed image with the original one.

In addition to PSNR values; processing time, brightness and contrast will be used as part of the computed analysis. Processing Time is the total time interval between image acquisition and getting the reconstructed image. Processing time may vary depending on the hardware and software that are used for the implementation. Brightness of original images will be set to zero and the change of the brightness in the reconstructed images will be calculated as in the equation

$$Brightness = \frac{Total\ gray\ values}{256*256}$$

$$\text{(Eq. 6)}$$

Contrast of the original and reconstructed images will be calculated using equation 2 to get the total change in contrast. Lowest change in contrast shows the least degradation of patterns within the images.

$$Contrast = \frac{\sum_{i,j}^{pixel\ size} org\ (Xij\ Yij) - Rec\ (Xij\ Yij)}{pixel\ size * pixel\ size}$$

$$\text{(Eq. 7)}$$

The results of the work will be obtained by the software developed by MATLAB simulation.
Future work will include the implementation of this intelligent system using discrete cosine transform. The results will be compared with the results from [3], which are obtained by using normal compression algorithms implemented by using MATLAB software. Figure 5 shows the training graph.

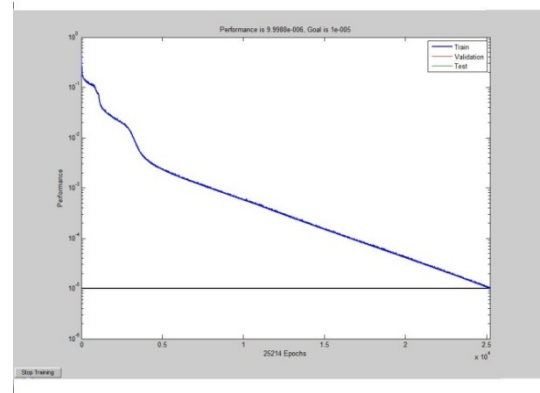Optimum compression ratios which are determined by the system is shown in table 2.

Figure 5: Training graph

Images and its visually inspected compression ratios are shown in the following table.

Table 1
Predetermined compression ratios

Image	ODCR in %	Image	ODCR in %
1_1	40	11_1	40
2_1	40	12_1	50
3_1	30	13_1	40
4_1	30	14_1	30
5_1	40	15_1	40
6_1	40	16_1	10
7_1	40	17_1	20
8_1	40	18_1	50
9_1	30	19_1	20
10_1	30	20_1	10

Table 2
ODCR given by the System

Testing Images	ODCR By system
Image 21	40 %
Image 22	40 %
Image24	50 %
Image 25	50 %

The designed system gives 100% accurate results for the trained image set. Accuracy for the above table is 75%. Out of 4 three ODCR are exact which are predetermined.

6. CONCLUSION

A novel method to intelligent image compression is proposed in this paper. The method uses DCT compression with nine compression ratios and a supervised neural network that learns to associate the grey image intensity (pixel values) with a single optimum compression ratio. The implementation of the proposed method uses lossy DCT image compression where the quality of the compressed images degrades at higher compression ratios. The aim of an optimum ratio is to combine high compression ratio with good quality compressed image.

Even though it is shown in above results that HWT and BWT shows better results, the rapid growth of digital imaging applications, including desktop publishing, multimedia, teleconferencing, and high-definition television (HDTV) has increased the need for effective and standardized image compression techniques. Among the emerging standards are JPEG, for compression of still images [Wallace 1991]; MPEG, for compression of motion video [Puri 1992]; and CCITT H.261 (also known as Px64), for compression of video telephony and teleconferencing, all three of these standards employ a basic technique known as the discrete cosine transform (DCT). So the intelligent system by using artificial neural network will be developed for DCT compression only.

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