INTELLIGENT SYSTEM FOR IMAGE COMPRESSION

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Abstract: The parallel processing capability of neural networks provides efficient means for processing images with large amount of data. Image compression using Discrete Cosine Transforms (DCT) is a lossy compression method where at higher compression ratios the quality of the compressed images is reduced, thus the need for finding an optimum compression ratio that combines high compression and good quality. This paper suggests that the image intensity can affect the choice of an optimum compression ratio. A neural network will be trained to establish the non-linear relationship between the image intensity and its compression ratios in search for an optimum ratio. Experimental results suggest that a trained neural network can relate image intensity or pixel values to its compression ratio and thus can be successfully used to predict optimum DCT compression ratios for different images.

1 INTRODUCTION

Image compression is one of these commonly used image processing applications where the rapid advance in multimedia applications has made data compression more vital and compression methods are being developed to compress large data files such as images (Nadenau etal., 2003). Efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size (Ratakonda and Ahuja, 2002).

Recently, adaptive prediction was suggested for data compression and still image coding (Robinson, 2006), and oriented wavelet transform for image compression was proposed (Chappelier and Guillemot, 2006). The use of wavelet transforms and Discrete Cosine Transform (DCT), when applied to image compression, was also investigated (Khashman and Dimililer, 2005). 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 programs is to compress images, but the result is less than optimal.

DCT-based image compression is a simple compression method that was first applied in 1974 (Ahmed etal., 1974). The disadvantage of using DCT image compression is the high loss of quality in compressed images, which is more notable at higher compression ratios. Recent work on finding optimum compression suggested a criterion based on visual inspection and computed analysis of the reconstructed images (Khashman and Dimililer, 2005). Visual inspection and observation by humans 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 (Jahne, 2002), (Khashman and Dimililer, 2005), i.e. the optimum compression ratio.

The use of neural networks for image processing applications has marginally increased in recent years, where image compression using DCT and a neural network was suggested previously (Ng and Cheng, 1997). More recently, different image compression techniques were combined with neural network classifiers for various applications (Zhou etal., 2006), (Milani, 2006). However, none of these methods suggested using a neural network to

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determine optimum compression using the original image intensity.

The aim of the work presented within this paper is to develop an intelligent system for optimum DCT image compression using a neural network. Our hypothesis is that a trained neural network can learn the non-linear relationship between the image intensity (pixel values) and its optimum compression ratio. Once trained, the neural network would predict the optimum compression ratio of an image upon presenting the image to the neural network by using its intensity values. The prediction parameters here are the image intensity (global pixel values) and the experience (training) of the neural network.

2 THE INTELLIGENT SYSTEM

The development and implementation of the proposed intelligent system for optimum DCT image compression uses 80 images that have different objects, brightness and contrast. The novel system is implemented in two phases: the image processing phase and the neural network arbitration phase.

2.1 Image Pre-Processing Phase

DCT-based image compression is firstly applied to all 80 images using 9 compression ratios (10%, 20%,… 90%) as shown in an example in Figure 1. The optimum DCT compression ratios for the 80 images are then determined using the optimum compression criteria based on visual inspection as suggested by (Khashman and Dimililer, 2005).

The image database is then organized as follows: 40 images in the training image set and 40 images in the testing image set which will be used to verify the efficiency of the proposed method. Figure 2 shows the examples of original images and their compressed versions using optimum compression ratios prior to training the neural network.

2.2 Neural Network Phase

The intelligent 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 database for training this supervised learner. The neural network consist of an input layer with 4096 neurons, one hidden layer with 82 neurons and an output layer with 9 neurons. Training the neural network uses 40 images which are grey and of size (256x256) pixels. Using Adobe Photoshop, the size of each image is initially reduced to (64x64) pixels prior to presenting the whole reduced image to the neural network, thus resulting in 4096 pixel values per image. Further reduction to the size of the images was attempted in order to reduce the number of input layer neurons and consequently the training time, however, meaningful neural network training could not be achieved, thus the use of whole images of size (64x64) pixels. The hidden layer of the neural network contains 82 neurons and he output layer has nine neurons according to the number of possible compression ratios (10% - 90%). Figure 3 shows the topology of this neural network where ODCR stands for optimum DCT Compression Ratio.

3 RESULTS AND DISCUSSION

The successful implementation of the proposed intelligent image compression system relies mainly on the learning capability of the neural network within the intelligent system. Meaningful learning and correct association of original images to their optimum compression ratios relies on the provision of sufficient input data patterns to the neural network during training and later on during generalization.

3.1 Neural Network Performance

The neural network learnt after 4447 iterations and within 3300 seconds. The running time for the generalized neural network after training and using

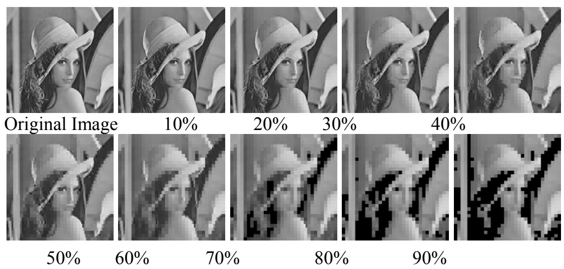

Figure 1: An image and its compression at nine ratios.

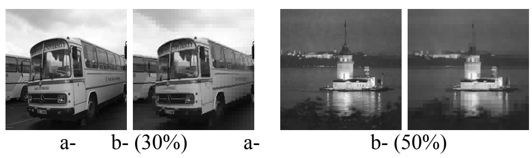

Figure 2: (a) Original images and (b) their optimum compressions.

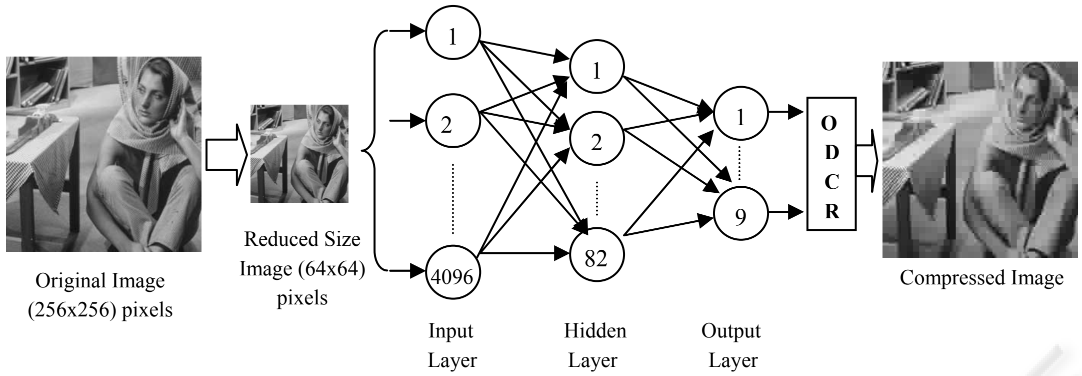

Figure 3: The intelligent optimum image compression system (ODCR: Optimum DCT Compression Ratio).

Table 1: Neural Network Final Training Parameters.

Input nodes	4096
Hidden nodes	82
Output nodes	9
Learning rate	0.0051
Momentum rate	0.49
Error	0.001
Iterations	4447
Training time (seconds)	3300
Run time (seconds)	0.003

Table 2: Accuracy and recognition rates for OCD.

OCD	Accuracy Rate (RA_{ODC})	Recognition Rate (RR_{ODC})
0	100 %	12/40 (30 %)
1	89 %	31/40 (78 %)
2	78 %	40/40 (100 %)

one forward pass was 0.003 seconds. These results were obtained using a 2.0 GHz PC with 2 GB of RAM, Windows XP OS and Matlab 7.1 software. Table 1 list the final parameters of the successfully trained neural network.

3.2 Evaluation Method

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:

$$RR_{ODC} = \left(\frac{I_{ODC}}{I_T} \right) * 100 \tag{1}$$

where RR_{ODC} is the recognition rate for the neural network within the intelligent 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:

$$RA_{ODC} = \left(1 - \frac{\left(\left| S_p - S_i \right| \right) * 10}{S_T} \right) * 100 \tag{2}$$

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

Table 2 shows the three considered OCD values and their corresponding accuracy rates and recognition rates.

The Optimum Compression Deviation (OCD) is another term that is used in our evaluation. *OCD* is the difference between the 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:

$$OCD = \left(\left| S_p - S_i \right| \right) * 10 \tag{3}$$

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

The evaluation of the intelligent system implementation results in this work uses ($OCD = 1$) and ($OCD = 2$) as they assure accuracy rates of 89% and 78% respectively, which is considered sufficient for this application. The trained neural network recognized correctly the optimum compression ratios for all 40 images in the training set as would be expected, thus yielding 100% recognition of the training set. Testing the trained neural network using 40 images that were not presented to the network before, yielded 78% recognition rate with 89%

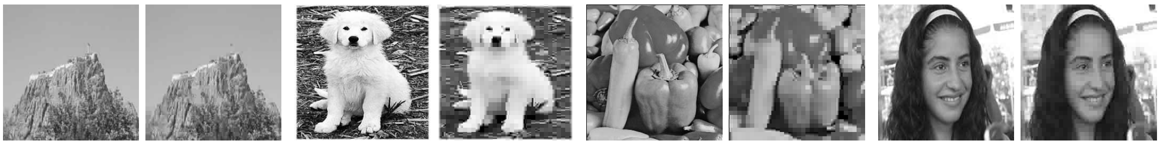

Figure 4: Examples of Optimum DCT compression results obtained using the trained neural network.

accuracy rate (using OCD=1), and 100% recognition rate with 78% accuracy rate (using OCD=2). Figure 4 shows examples of the optimally compressed images as determined by the trained neural network.

4 CONCLUSIONS

This paper proposed a novel method for optimum image compression that uses DCT compression and a neural network. The method suggests that a trained supervised neural network can learn the non-linear relationship between the intensity (pixel values) of an image and its optimum compression ratio, and thus can predict the optimum DCT compression ratio of an image upon presenting the original image to the trained neural network. 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 quality compressed image.

The proposed intelligent system that is presented within this paper was implemented using 80 images of various objects, contrasts and intensities. The neural network within the intelligent system learnt to associate 40 images with their different optimum compression ratios within 3300 seconds. Once trained, the neural could predict the optimum compression ratio of an image within 0.003 seconds upon presenting the image to the network.

The trained system uses three minimum accuracy levels which are determined depending on the application. In this work, minimum accuracy levels of 78% and 89% were used, where; 100% and 78% recognition rates of correct optimum compression ratio were obtained, respectively. This successful implementation of our proposed method was shown throughout the high recognition rate and the minimal time cost when running the trained neural network.

Future work will include the development of an intelligent optimum image compression system using Haar and Biorthogonal wavelet transform compressions which produce higher quality compressed images. Additionally, the intelligent system development will use larger image database.

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