OPTIMUM DCT COMPRESSION OF MEDICAL IMAGES USING NEURAL NETWORKS

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Abstract: Medical imaging requires storage of large quantities of digitized data Efficient storage and transmission of medical images in telemedicine is of utmost importance however,. Due to the constrained bandwidth and storage capacity, a medical image must be compressed before transmission or storage. An ideal image compression system must yield high quality compressed images with high compression ratio; this can be achieved using DCT-based image compression, however the contents of the image affects the choice of an optimum compression ratio. In this paper, a neural network is trained to relate the x-ray image contents to their optimum compression ratio. Once trained, the optimum DCT compression ratio of the x-ray image can be chosen upon presenting the image to the network. Experimental results suggest that out proposed system, can be efficiently used to compress x-rays while maintaining high image quality.

1 INTRODUCTION

X-rays or radiographs are images produced on a radiosensitive surface, such as a photographic film, by radiation other than visible light, especially by x-rays passed through an object or by photographing a fluoroscopic. These images, commonly referred to as x-rays, are usually used in medical diagnosis, particularly to investigate bones, dental structures, and foreign objects within the body. X-rays are the second most commonly used medical tests, after laboratory tests.

Recently, teleradiology, which is one of the most used clinical aspects of telemedicine, has received much attention. Teleradiology is the transmission of radiologic images from a site of image acquisition to a remote location for interpretation in hospitals such as computerized tomography (CT) scans, magnetic imaging (MRI), ultrasonography (US), and x-rays. These radiological images are needed to be compressed before transmission to a distant location or due to the bandwidth or storage limitations (Singh et al., 2007).

There has been a rapid development in compression methods to compress large data files such as images where data compression in various applications has become more vital (Nadenau et al., 2003). Efficient methods of compression, to compress and store or transfer image data files while retaining high image quality and marginal reduction in size are needed due to the improvements of technology (Ratakonda and Ahuja, 2002).

The discrete cosine transform (DCT) is possibly the most popular transform used in compression of images in standards like Joint Photographic Experts Group (JPEG). In DCT-based compression the image is split into smaller blocks for computational simplicity. The blocks are classified on the basis of information content to maximize compression ratio without sacrificing diagnostic information (Singh et al., 2007). DCT-based medical image compression has been investigated by several researchers. For example, in (Chikouche et al., 2008) DCT-based compression was applied to IRM type medical images. In (Prudhvi Raj and Venkateswarlu, 2007) a medical image compression application based on 3-dimensional DCT was proposed. In (Zukoski et al., 2006) region based medical image compression has been applied to choose the clinically relevant regions as defined by radiologists. In (Shih and Wu, 2005) another region of interest based medical image compression based on genetic algorithms was also investigated.

The use of DCT and artificial neural networks has also been investigated in search for optimum compression methods. In (Dokur, 2008) MR and CT medical images were compressed using DCT and neural networks. In (Ashraf and Akbar, 2006)

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another application of neural networks in medical image compression was also proposed. In (Meyer-Base et al., 2005) topology-preserving neural networks were applied for medical image compression by a ‘‘neural-gas’’ network. In (Liying and Khashayar, 2005) different image compression techniques were combined with neural network classifier for various applications. In (Soliman and Omari, 2006) a neural network model called direct classification was also suggested to compress image data. In (Ciernak, 2004) periodic vector quantization algorithm based image compression was suggested and was based on competitive neural networks quantizer and neural networks predictor.

More works using neural networks for image compression applications emerged lately, such as those in (Ashraf and Akbar, 2005), (Northan and Dony, 2006), (Vilovic, 2006), and (Veisi and Jamzad, 2007). Recently, a neural network based DCT compression system that finds the optimum compression ratios for a variety of images was also suggested (Khashman and Dimililer, 2007), where the evaluation method of the neural network-obtained optimum compression results was based on the comparison criteria; which was suggested in (Khashman and Dimililer, 2005).

The aim of the work presented within this paper is to develop a medical image compression system using Discrete Cosine Transform and a neural network. Our proposed method suggests that a trained neural network can learn the non-linear relationship between the intensity (pixel values) of an x-ray image and its optimum compression ratio.

Once the highest compression ratio is obtained, while maintaining good image quality, the result reduction in x-ray image size, should make the storage and transmission of x-rays more efficient, thus providing compressed images with good quality and satisfactory information for the medics.

The paper is organized as follows: Section 2 describes the x-ray image database which is used for the implementation of our proposed system. Section 3 presents the x-rays compression system; describing image pre-processing and the neural network design and implementation. Section 4 introduces the method used to evaluate the results and provides an analysis of the system implementation. Finally, Section 5 concludes the work that is presented within this paper and suggests further work.

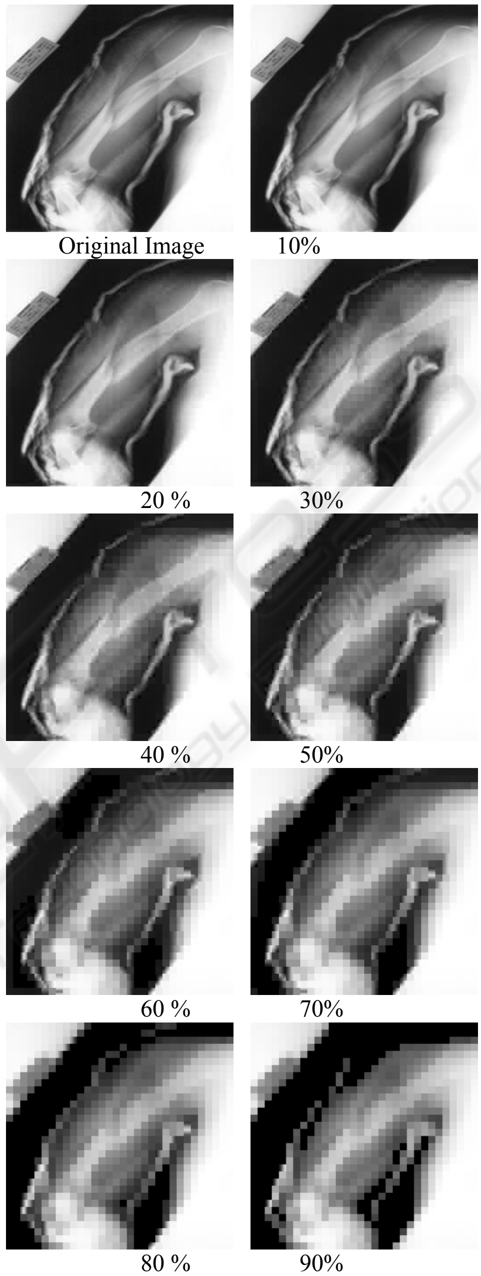

Figure 1: An original x-ray image and its DCT compression at nine ratios.

2 X-RAY IMAGE DATABASE

The development and implementation of the proposed medical x-rays compression system uses 60 x-ray images from our medical image database which were obtained from the Radiology Department at the Famagusta General Hospital (Famagusta, Cyprus), which contains x-ray images of fractured, dislocated, broken, and healthy bones in different parts of the body. DCT compression has been applied to 50 radiographs using nine compression ratios (10%, 20%, ..., 90%) as shown in an example in Figure 1.

The optimum DCT compression ratios for the 50 x-ray images were determined using the optimum compression criteria based on visual inspection of the compressed images as suggested in (Khashman and Dimililer, 2005), thus providing 50 images with *known* optimum compression ratios and the remaining 10 images with *unknown* optimum compression ratios. The image database is then organized into three sets:

- Training Set: contains 25 images with *known* optimum compression ratios which are used for training the neural network within the radiograph compression system. Examples of training images are shown in Figure 2a.
- Testing Set 1: contains 25 images with *known* optimum compression ratios which are used to test and validate the efficiency of the trained neural network. Examples of these testing images are shown in Figure 2b.
- Testing Set 2: contains 10 images with *unknown* optimum compression ratios which are used to further test the trained neural network. Examples of these testing images are shown in Figure 2c.

Examples of original x-ray images and their compressed versions using their optimum compression ratios while training the neural network are shown in Figure 3.

3 X-RAY IMAGE COMPRESSION SYSTEM

The optimum x-ray 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 neural network relates the x-ray 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 choose the optimum compression ratio of an x-ray image upon presenting it to the neural network by using its intensity values.

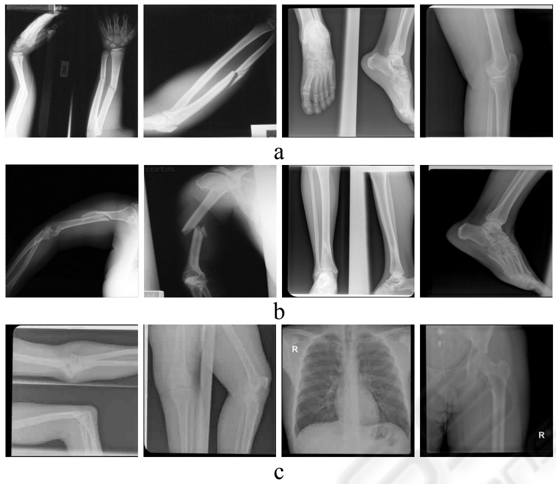

Figure 2: (a) Training Set examples (b) Testing Set 1 examples, (c) Testing Set 2 examples.

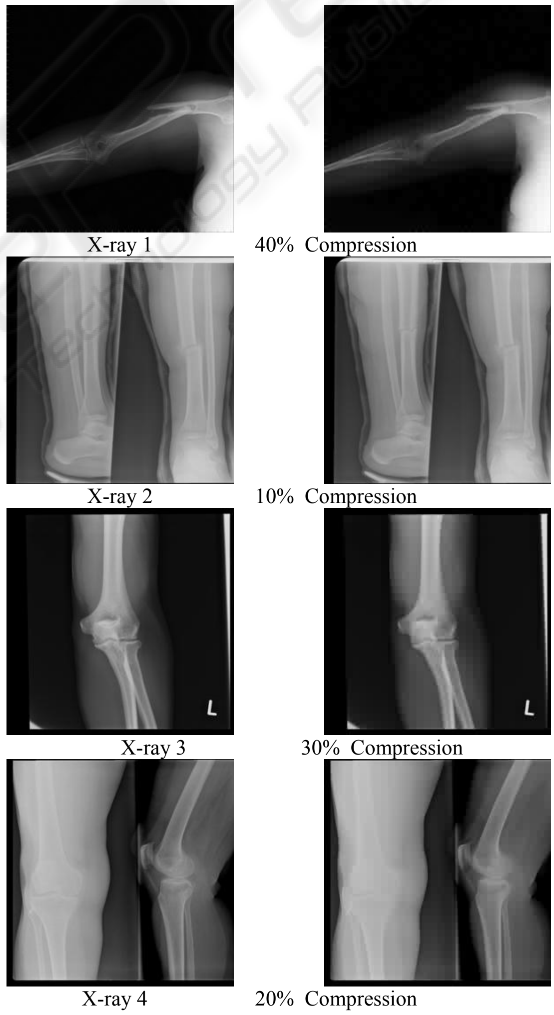

Figure 3: Examples of Training Set images and their optimum compression ratios.

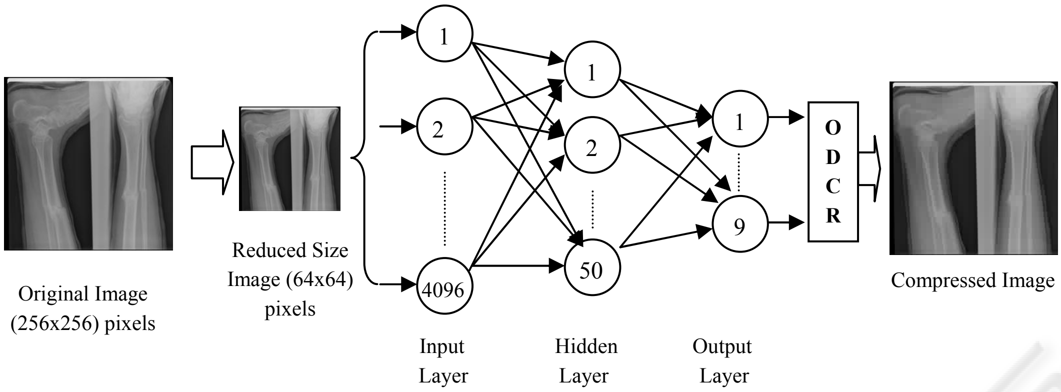

Figure 4: X-ray Image Compression System.

Adobe Photoshop was used to resize the original images of size (256x256) pixels into (64x64) pixels. 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 the reduced size of 64x64 pixels.

The size of the input x-ray images affects the choice of the number of neurons in the neural network's input layer, which has three layers; input, hidden and output layers. Using one-pixel-per-neuron approach, the neural network's input layer has 4096 neurons, its hidden layer has 50 neurons, which assures meaningful training while keeping the time cost to a minimum, and its output layer has nine neurons according to the number of the considered compression ratios (10% - 90%).

During the learning phase, the learning coefficient and the momentum rate were adjusted during various experiments in order to achieve the required minimum error value of 0.003; which was considered as sufficient for this application. Figure 4 shows the topology of this neural network, within the x-ray image compression system.

4 RESULTS AND DISCUSSIONS

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: where RR_{OHC} is the recognition rate for the neural network within the radiograph compression system, I_{OHC} is the number of optimally compressed x-ray images, and I_T is the total number of x-ray images in the database set.

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

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

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

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:

$$OCD = \left(\left| S_p - S_i \right| \right) * 10 \qquad (3)$$

The OCD is used to indicate the accuracy of the system, and depending on its value the recognition rates vary. Table 1 shows the three considered values of OCD and their corresponding accuracy rates and recognition rates. The evaluation of the system implementation results uses (*OCD = 1*) as it provides a minimum accuracy rate of 89% which is considered sufficient for this application.

The neural network learnt and converged after 2960 iterations or epochs, and within 774 seconds, whereas the running time for the generalized neural networks after training and using one forward pass was 0.015 seconds. These results were obtained using a 2.0 GHz PC with 2 GB of RAM, Windows XP OS and Matlab 2008b software. Table 2 lists the final parameters of the successfully trained neural network, whereas Figure 5 shows the error minimization curve of the neural network during learning.

Table 1: Accuracy and recognition rates for OCD.

OCD	Accuracy Rate (RA_{ODC})	Recognition Rate (RR_{ODC})
0	100 %	15/25 (60 %)
1	89 %	24/25 (96 %)
2	78 %	25/25 (100 %)

Table 2: Neural network final training parameters.

Input nodes	4096
Hidden nodes	50
Output nodes	9
Learning rate	0.003
Momentum rate	0.4
Error	0.003
Iterations	2960
Training time (seconds)	774
Run time (seconds)	0.015

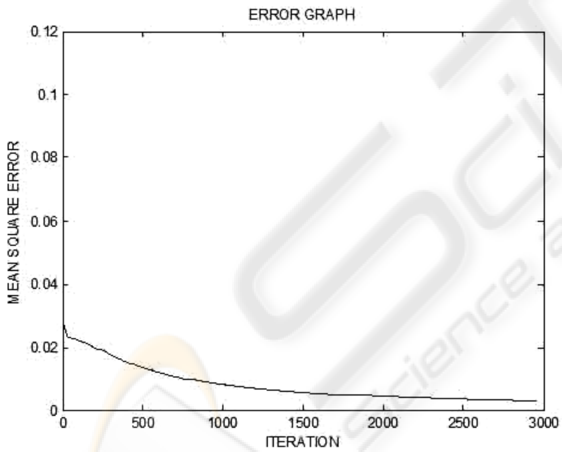

Figure 5: Neural network learning curve.

The trained neural network recognized correctly the optimum compression ratios for all 25 training images as would be expected, thus yielding 100% recognition of the training set. Testing the trained neural network using the 25 images from Test Set 1 that were not presented to the network before yielded 96% recognition rate, where 24 out of the 25 images with known optimum compression ratios were assigned the correct ratio.

The trained neural network was also implemented using the remaining 10 images with unknown optimum compression ratios from the testing set. The results of this application are demonstrated Figure 6 which shows examples of the optimally compressed x-ray images as determined by the trained neural network.

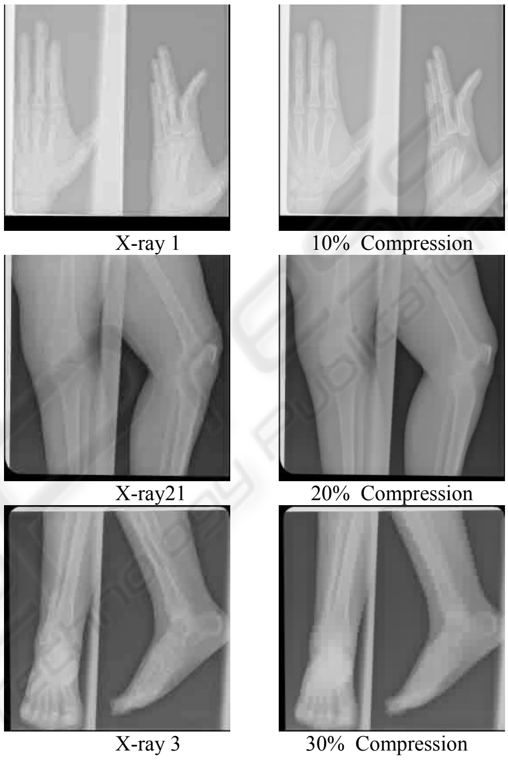

Figure 6: Examples of Testing Set 2 image compression using the trained neural network.

5 CONCLUSIONS

A novel method to medical x-ray image compression using a neural network is proposed in this paper. The method uses DCT-based compression with nine compression ratios and a supervised neural network that learns to associate the grey x-ray image intensity (pixel values) with a single optimum compression ratio.

The implementation of the proposed method uses DCT image compression where the quality of the compressed images degrades at higher compression ratios due to the nature of the lossy compression. The aim of an optimum ratio is to combine high compression ratio with good quality compressed x-ray images, thus making the storage and transmission of images more efficient.

The proposed system was developed and implemented using 60 x-ray images of fractured, dislocated, broken, and healthy bones in different parts of the body. The neural network within the x-ray image compression system learnt to associate the 25 training images with their predetermined optimum compression ratios within 774 seconds. Once trained, the neural network could recognize the optimum compression ratio of an x-ray image within 0.015 seconds

In this work, a minimum accuracy level of 89% was considered as acceptable. Using this accuracy level, the neural network yielded 96% correct recognition rate of optimum compression ratios. The successful implementation of our proposed method using neural networks was shown throughout the high recognition rates and the minimal time costs when running the trained neural network.

Future work will include the implementation of this method using wavelet transform compression and comparing its performance with DCT-based x-ray image compression using larger database.

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