X-RAY IMAGE COMPRESSION USING NEURAL VETWORKS

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ABSTRACT

Neural Networks are based on the parallel architecture and are inspired from human brains. Neural networks are a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, simple scalar messages and adaptive interaction between elements. One such application is image compression. Image compression is a process which minimizes the size of an image file without degrading the quality of the image to an unacceptable level. It also reduces the time required for images to be sent over the internet or downloaded from web pages. Efficient storage and transmission of medical images in telemedicine is of utmost importance however, this efficiency can be hindered due to storage capacity and constraints on bandwidth. Thus, a medical image may require compression before transmission or storage. Ideal image compression systems must yield high quality compressed images with high compression ratio; this can be achieved using wavelet transform based compression, however, the choice of an optimum compression ratio is difficult as it varies depending on the content of the image. In this paper, a neural network is trained to relate radiograph image contents to their optimum image compression ratio. Once trained, the neural network chooses the best wavelet compression ratio of the x-ray images upon their presentation to the network. Experimental results suggest that our proposed system can be efficiently used to compress radiographs while maintaining high image quality.

Keywords. X-ray image, comperession, neural networks.

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1. INTRODUCTION

Images play an important role in the world of multimedia and its transmission with storage has become really a big burden as it occupies more space in memory, [9]. The goal of image compression is to create smaller files that use less space to store and less time to send, [11,13]. Image compression involves reducing the size of image data files, while retaining necessary information, [15-19]. Hence, it is essential to analyze and suggest a best technique for lossless image compression, [20].

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 attempts to transfer medical images of various modalities, like computerized tomography (CT) scans, magnetic imaging (MRI), ultrasonography (US), and x-rays from one location to another such as in hospitals, imaging centers or a physician's desk. The radiological images need to be compressed before transmission to a distant location or due to the bandwidth or storage limitations [1]. There has been a rapid development in compression methods to compress large data files such as images where data compression in various applications has lately became more vital [2]. With the improvements of technology, efficient methods of compression are needed to compress and store or transfer image data files while retaining high image quality and marginal reduction in size [3]. Wavelets are a mathematical tool for hierarchically decomposing functions. There is a general preference to use wavelet transforms in image compression because the compressed images can be obtained with higher compression ratios and higher PSNR values [4].Unlike the discrete cosine transform, the wavelet transforms are not Fourier based and therefore discontinuities in image data can be handled with better results using wavelets [5]. The aim of the work presented within this paper is to develop medical radiographs compression system using best wavelet transform and a neural network. The proposed method suggests that a trained neural network can study the non-linear relationship between the intensity (pixel values) of a radiograph, or x-ray image and its optimum compression ratio. Once the highest compression ratio is obtained, while maintaining good image quality, the result reduction in radiograph image size, should make the storage and transmission of radiographs more efficient.

2. WAVE & WAVELETS

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited for the analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy. The Discrete wavelet transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and to reduce the computation time and resources required. A sampled input image is decomposed into various frequency sub bands or sub band signals. A two dimensional decomposition can be applied over the image. A simple example of level 2Decomposing is shown in Fig 1. The original image is subdivided into four parts. The LL band contains low frequency contents of the signal, whereas, HH band contains high frequency contents of the signal, which has less importance than LL band.

3. NEURAL NETWORKS

Neural networks are simplified models of the biologic neuron system and therefore, have drawn their motivation from the computing performed by a human brain [10] [14] [18]. A neural network, in general, is a highly interconnected network of a large number of processing elements called neurons in an architecture inspired by the brain [2,17]. Artificial neural networks are massively parallel adaptive networks of simple nonlinear computing elements called neurons which are intended to abstract and model some of the functionality of the human nervous system in an attempt to partially capture some of its computational strengths, [19,20]. A neural network can be viewed as comprising eight components which are neurons, activation state vector, signal function, pattern of connectivity, activity aggregation rule, activation rule, learning rule and environment, [17].

4. NEED FOR IMAGE COMPRESSION

Images are stored on computers as collections of bits representing pixels, forming the picture elements. Many pixels are required to store even moderate quality images. Image compression plays a pivot role in diminishing this amount of information. Most images contain some amount of redundancy that can sometimes be removed when the image is stored and replaced when it is reconstructed, but the original symbols, [11] and [16] eliminating this redundancy does not lead to high compression. The amount of data associated with visual information is so large that its storage would require enormous storage capacity. So image compression is very important to reduce the storage and transmission costs while maintaining good quality. Image compression is the process of effectively coding digital images to reduce the number of bits required in representing an image. If the compression is effective, the resulting stream of codes will be smaller than the original symbols, [11, 16 and 18].

5. BEST WAVELETS SELECTION

The best wavelet can be obtained by using the picture quality measures & the parameters obtained by applying the different wavelets compression techniques to our database

6. IMAGE COMPRESSION METHOD

Image Compression has been pushed to the forefront of the image processing field. This is largely a result of the rapid growth in computer power, the corresponding growth in the multimedia market, and the advent of the World Wide Web, which makes the internet easily accessible for everyone. Compression algorithm development starts with applications to two-dimensional (2-D) still images. Because video and television signals consist of consecutive frames of 2-D image data, the development of compression methods for 2-D still is

dataof paramount importance, [9,11,14 and16]. The goal of image compression is to create smaller files that use less space to store and less time to send. Image compression involves reducing the size of image data files, while retaining necessary information. The reduced file is called the compressed file and is used to reconstruct the image, resulting in the decompressed image. The original image, before any compression is performed, is called the uncompressed image file. The ratio of the original, uncompressed image file and the compressed file is referred to as the compression ratio. The compression ratio, [13] is denoted by:

$$\text{Compression Ration} = \frac{size\ of\ the\ output\ file}{size\ of\ the\ input\ file}$$

$$\text{Transmission Time} = \frac{number\ of\ pixels\ Xnumber\ of\ Bit/pixels}{Modem\ speed(Kilobits/\ second)}$$

$$\text{Compression performance} = 100*(1 - \text{compression ration})$$

The basic types of image compression methods are Lossless compression method and Lossy compression method. Lossless compression is a compression without any loss of image quality. This means that the compression method will not cause any loss of data or errors. This is possible because all read data contain repeating patterns of some sort that a compression processor can search out and then arrange to transmit more efficiently. Generally these methods are used in applications where the loss of even a single bit is dangerous, [15,16].

In order to achieve high compression ratios with complex images, lossy compression methods are required. Lossy compression provides tradeoffs between image quality and degree of compression, which allows the compression algorithms to be customized to the application. With some of more advanced methods, images can be compressed 10 to 20 times with virtually no visible information loss, and 30 to 50 times with minimal degradation. Image enhancement and restoration techniques can be combined with Lossy compression schemes to improve the appearance of the decompressed image. In general, a higher compression ratio results in a poorer image, but the results are highly image dependent. A technique that works well for one application may not be suitable for another.

Lossy compression is a compression with loss of image quality. In this compression method, the image is not an exact replacement of the original image, [17,20].

7. RADIOGRAPH DATABASE

The development and implementation of the proposed medical radiograph compression system uses 70 x-ray images from our medical image database, [25], which contains radiographs of fractured, dislocated, broken and healthy bones in different parts of the body. Wavelet compression has been applied to 50 radiographs using different wavelet methods as shown in an example in Fig. 3. The best wavelet compression for the 50 radiographs were determined using the optimum compression criteria based on visual inspection of the compressed images as suggested in [6], thus providing 50 images with known optimum compression ratios and the remaining 20 images with unknown optimum compression ratios. The image database is then organized into three sets:

1- Training image set: contains 30 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 Fig. 4a.

2- Testing image set 1: contains 20 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 Fig. 4b.

3- Testing image set 2: contains 20 images with unknown optimum compression ratios which are used to further test the trained neural network. Examples of these testing images are shown in Fig. 4c.

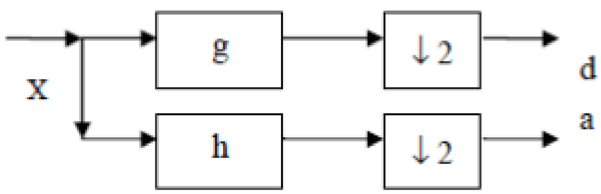

Figure. 1 Splitting of signal into two parts

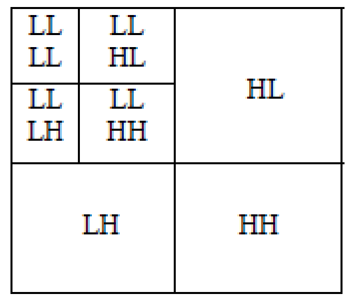

Figure. 2 Splitting of signal into two parts

Table 1: Picture Quality Measure

Mean Square Error : MSE	$= \frac{1}{N}\sum_{J=1}^{N}\sum_{K=1}^{M}\left[X_{J,K} - \bar{X}_{J,K}\right]^2$
Peak Signal to noise Ration : PSNR	$=10\log\frac{(2^n-1)^2}{MSE} = 10\log\frac{255^2}{MSE}$
Normalized Cross Correlation : NCC	$=\sum_K^N\sum_K^M X_{J,K} * \overline{X_{J,K}} / \sum_J^N\sum_K^M {X_{J,K}}^2$
Average Difference : AD	$=\sum_J^N\sum_K^M\frac{(X_{J,K} - \overline{X_{J,K}})}{MN}$
Maximum Difference : MD	$=\mathrm{MAX}\left(\left\|X_{J,K} - \overline{X_{J,K}}\right\|\right)$
Normalized Average Error : NAE	$=\sum_J^N\sum_K^M\frac{\|X_{J,K}-\overline{X_{J,K}}\|}{\sum_J^N\sum_K^M\|X_{J,K}\|}$

Table 2: Compressed Image Parameters

Wavelet	THR	CR	MSE	PSNR	MD	MD	MDAD	NAE	NCC
haar	28	60.0230	4.99515	94.811	29	1.000451	-2.2E-14	0.013486	0.999548
db1	28	60.0230	4.99515	94.81	29	1.000451	-2.2E-14	0.013486	0.999548
db2	1	60.0064	0.074166	136.9181	1.70658	1.000007	4.11E-05	0.002145	0.999993
bior1.1	28	60.0230	4.995115	94.81811	29	1.000451	-2.2E-14	0.013486	0.999548
bior1.3	10.5	60.0620	2.6058	101.3262	12.5	0.999886	-2.2E-41	0.011241	0.999939
bior4.4	0.782	60.0091	0.050849	140.6926	1.37482	1.000004	-5.4E-05	0.0018	0.999996
bior6.8	0.757	60.0535	0.048468	141.172	1.17028	1.000004	-3.9E-	0.001795	0.999996
rbio1.1	28	60.0230	4.995115	94.81811	29	1.000451	-2.2E-14	0.013486	0.999548
rbio1.3	0.875	60.0023	0.060113	139.0188	1.21875	1.000006	-2.3E-14	0.001961	0.999994
coif1	0.93	60.0784	0.064784	138.2704	1.53568	1.000006	3.33E-05	0.002006	0.999994
coif2	0.84	60.0754	0.054985	139.9104	1.27813	1.000004	-3E-05	0.001891	0.999995
sym30	0.755	60.3127	0.046654	141.5535	1.19289	1.000005	1.94E-05	0.001806	0.999995
rbio1.1	28	60.0230	4.995115	94.81811	29	1.000451	-2.2E-14	0.013486	0.999548

Original compressed (thr=80)

Haar

Original compressed (thr=80)

Coifflet

Original compressed (thr=80)

Biorthogonal

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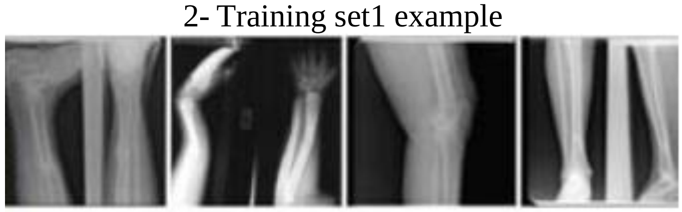
Fig.3- Compression using different wavelets

8. RADIOGRAPH COMPRESSION SYSTEM

The optimum radiograph 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 of the supervised learner. The neural network relates the xray 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 the radiographs that require pre-processing prior to presenting them to the neural network; a radiograph upon presenting it to the neural network by using its intensity values.

1-Training set example

2- Training set1 example



3-Training set 2 example

Fig:4- Radiograph Database Example

Pre-processing the x-rays aims to reduce the amount of necessary data from images while maintaining meaningful representation of the contents of the radiographs. Adobe Photoshop was used to resize the original radiographs of size (256 x 256) pixels into (64 x 64) 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%).

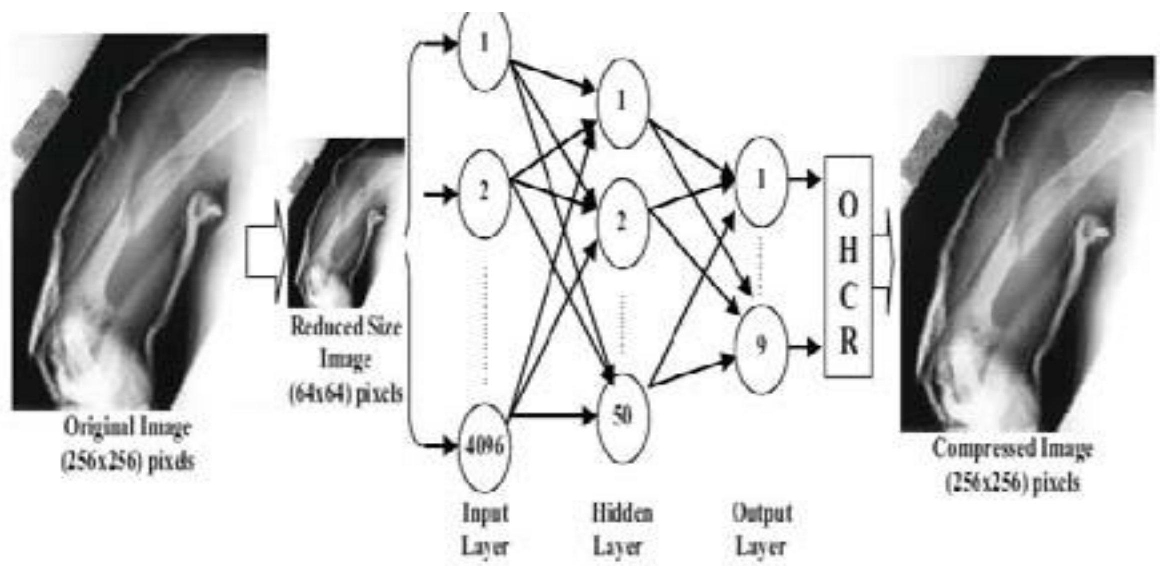


Fig5. Radiograph compression system.

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 0.005; which was considered as sufficient for this application. Fig 5, shows the topology of this neural network, within the radiograph compression system.

9. RESULTS AND DISCUSSIONS

The best wavelet was found as biorthogonal 6.8 for x-ray image compression by visualization 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:

$$RR_{OHC}=\frac{(IOHC)}{IT} *100$$

where RROHC is the recognition rate for the neural network within the radiograph compression system, IOHC is the number of optimally compressed x-ray images, and IT is the total number of x-ray images in the database set. The accuracy rate RAOHC for the neural network output results is defined as follows:

$$RA_{OHC} =\left(1-\frac{(S_P-S_I)*10}{S_T}\right) *100$$

Where, SP represents the pre-determined (expected) optimum compression ratio in S_I percentage, represents the optimum compression ratio as determined by the trained neural network

$inpercentage\ and\ ST\ represents\ the\ total\ number\ of\ compression\ ratios. The\ Optimum$ Compression Deviation (OCD) is another term that is used in our valuation. OCD is the difference between the pre-determined or expected optimum compression ratio SP and the optimum compression ratio Si as determined by the trained neural network, and is defined as follows:

$$\text{OCD} =(|S_P - S_I| * 10)$$

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 neural network studied and converged after 1000 iterations or epochs, and within 241.37 seconds, whereas the running time for the generalized neural networks after training and using one forward pass was 0.006 seconds. These results were obtained using a 2.0 GHz PC with 2 GB of RAM, Windows XP OS and Matlab 2010b software. Table.1 lists the final parameters of the successfully trained neural network. Fig.7, shows the error minimization curve of the neural network during the studying process.

Table 3. Trained neural network final parameters

Input neurons	**6409.0**
Hidden neurons	**50.000**
Output neurons	**9.000**
Epoch	**87.000**
Time	**241.00**
MSE	**0.0048**

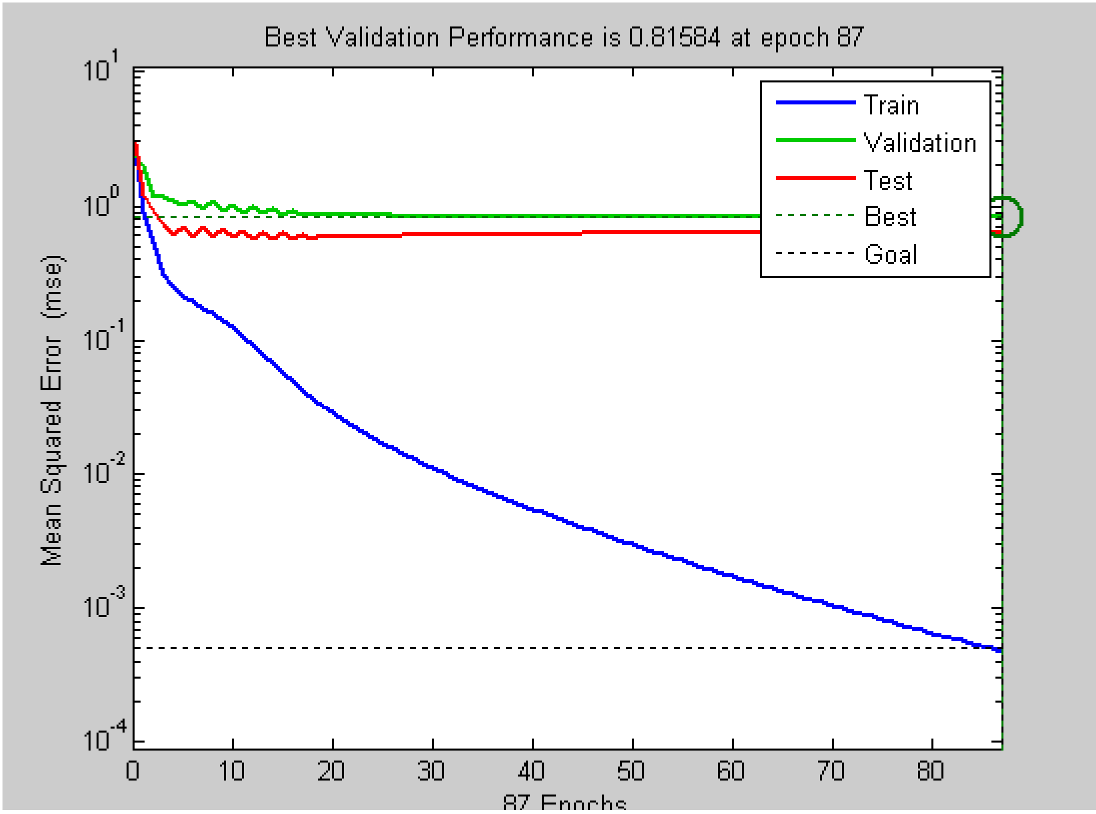


Fig8. Neural network learning curve

10. CONCLUSION

A novel method to medical radiograph compression using a neural network is proposed in this paper. The method uses Best wavelet compression with given threshold, wavelet type and a supervised neural network that learns to associate the grey x-ray image intensity (pixel values) with a given threshold and picture quality measures. The implementation of the proposed method uses Best wavelet X-ray image compression where the quality of the compressed images degrades at higher compression ratios due to the nature of the Lossy wavelet compression. The aim of an optimum ratio is to combine high compression ratio with good quality compressed radiograph, thus making the storage and transmission of radiographs more efficient The proposed system was developed and implemented using 70 radiographs or x-ray images of fractured, dislocated, broken, and healthy bones in different parts of the body. The neural network within the radiograph compression system was studied to associate the 50 training x-ray images with their predetermined optimum compression ratios within 241.43 seconds. Once trained, the neural network could recognize the optimum compression ratio of an x-ray image within 0.006 seconds. In this work, a minimum accuracy level of 89% was considered as acceptable. Using this accuracy level, the neural network yielded 98.65% correct recognition rate of optimum compression ratios. The successful implementation of the proposed method, using neural networks was shown throughout the high recognition rates and the minimal time costs when running the trained neural networks. Future work will include the implementation of this method using image compression using Zapak technique and comparing its performance with Bi-orthogonal 6.8 radiograph compression.

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