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Research Article

MEDICAL RADIOGRAPH COMPRESSION USING NEURAL NETWORKS AND HAAR WAVELET

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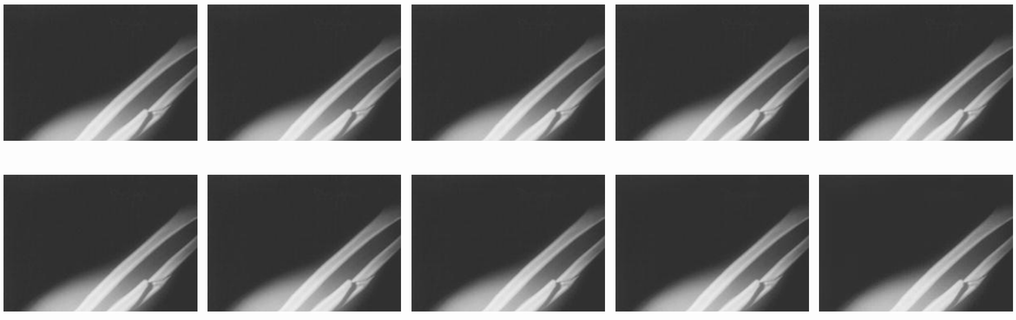
Abstract

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 ideal Haar 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.

I. Introduction

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 are needed 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 and 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]. Haar wavelet transform is one of the wavelet methods applied in compressing the digital images. Previous works using haar image compression include an application that is applied to adaptive data hiding for the images dividing the original image into 8x8 sub-blocks and reconstructing the images after compression with good quality [6], and the use of Parametric Haar-like transform that is based on a fast orthogonal parametrically adaptive transform such that it may be computed with a fast algorithm in structure similar to classical haar transform [7]. The use of compression methods in general, and wavelet compression in particular, with medical images has been previously investigated. For example, in [1] an adaptive approach for the classification of blocks on the basis of an adaptive threshold value of variance, was presented and applied to different medical images such as CT, X- ray and ultrasound images. In [8] a compression algorithm for far infrared medical images was proposed based on lifting wavelet transform and histogram shifting. In [9] an algorithm to compress and to reconstruct Digital Imaging and Communications in Medicine (DICOM) images. Their algorithm consisted of two stages: DICOM images were first decomposed using generalized Cohen-Daubechies-Feauveau biorthoganal wavelet and the wavelet coefficients were encoded using Set Partitioning In Hierarchical Trees (SPIHT). In [10] an image compression scheme, using the discrete wavelet transformation (DWT) and the k-means clustering technique, was suggested and applied to medical images. In [11] a method based on topology- preserving neural networks was used to implement vector quantization for medical image compression .



Original Image 10% 20% 30% 40%
50% 60% 70% 80% 90%

Fig.1 – An original radiograph and its Haar compression at nine ratios.

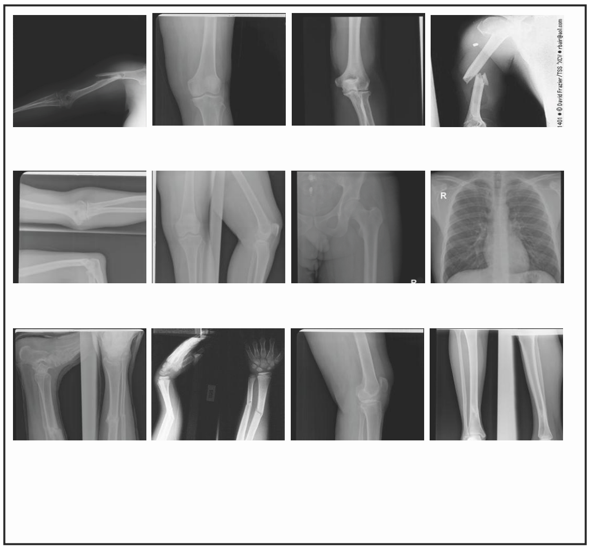
In [12] A lossless wavelet-based image compression method with adaptive prediction was proposed, and applied to achieve higher compression rates on CT and MRI images. In [13] a combining technique for image compression based on the Hierarchical Finite State Vector Quantization (HFSVQ) and a neural network, was proposed and applied to medical images. Artificial neural networks implementations in image processing applications has marginally increased in recent years. Image compression using wavelet transform and a neural network was suggested previously[14]. Moreover, different image compression techniques were combined with neural network classifier for various applications [15]. A neural network model called direct classification was also suggested; this is a hybrid between a subset of the self-organising Kohonen model and the adaptive resonance theory model to compress the image data [6]. Periodic Vector Quantization algorithm based image compression was suggested previously based on competitive neural networks quantizer and neural networks predictor [7]. More works using neural networks emerged lately. In [8] a Multi-Resolution Neural Network (MRNN) filter bank was used as a transform for coding. In [9] an image compression algorithm based on image blocks complexity measure methods and a neural network was proposed. In [10] a direct solution method applied to image compression using neural networks was suggested. In [11] a Principal Component Analysis based neural network was used for image compression. In [12] a neural network quantizer was used to yield a high compression ratio while maintaining high quality images.

Recently, a neural network based DCT compression system that finds the optimum compression ratios for a variety of images was also suggested [14]. The evaluation method of the neural network-obtained optimum compression results was based on the comparison criteria; which was suggested in [14]. More recently, a neural network model was used to obtain the optimum compression ratio when using Haar wavelet image compression which was applied to a variety of images [5]. The aim of the work presented within this paper is to develop a medical radiographs compression system using Haar wavelet transform and a neural network.

The proposed method suggests that a trained neural network can learn 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. The paper is organized as follows: Section II describes the radiograph database which is used for the implementation of our proposed system. Section III presents the radiograph compression system; describing the x-ray image pre-processing and the neural network design and implementation. Section IV introduces the method used to evaluate the results and provides an analysis of the system implementation. Finally, Section V concludes the work that is presented within this paper and suggests further work.

II. Radiograph Database

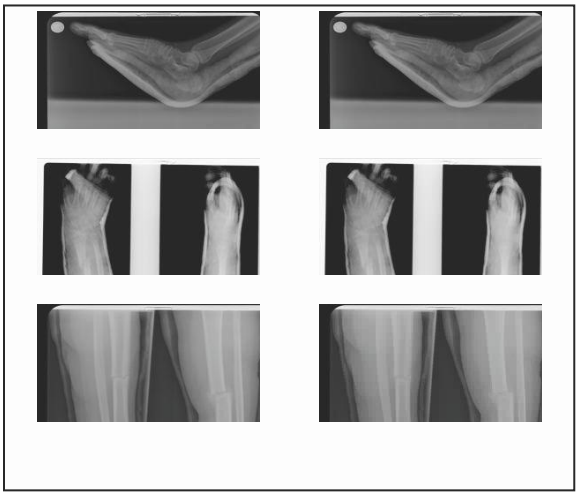
The development and implementation of the proposed medical radiograph compression system uses 60 x-ray images from our medical image database [15], which contains radiographs of fractured, dislocated, broken, and healthy bones in different parts of the body. Haar wavelet compression has been applied to 48 radiographs using nine compression ratios (10%, 20%,., 90%) as shown in an example in Fig. 1.



a- Training set examples, b- Testing Set 1 examples, c- Testing Set 2 examples

Fig.2 – Radiograph database examples.

Radiograph 1 70 % Compressed



Radiograph 2 80 % Compresse

Radiograph 3 90 % Compressed

Fig.3 – Examples of Training set radiographs and their optimum Haar compression.

The optimum Haar compression ratios for the 48 radiographs were determined using the optimum compression criteria based on visual inspection of the compressed images as suggested in [7], thus providing 48 images with known optimum compression ratios and the remaining 12 images with unknown optimum compression ratios. The image database is then organized into three sets:

Training Image 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 Fig. 2a.

Testing Image Set 1: contains 23 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. 2b.

Testing Image Set 2: contains 12 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. 2c.

Examples of original radiographs and their compressed versions using their ptimum compression ratios while training the neural network are shown in Fig. 3.

III. 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 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 a radiograph upon presenting it to the neural network by using its intensity values. The radiographs require pre-processing prior to presenting them to the neural network. 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 (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 compression ratio S_i as determined by the trained neural network, and is defined as follows: Error value of 0.005; which was considered as sufficient for this application. Fig. 4 shows the topology of this neural network, within the radiograph compression system.

$OCD = (|S_p - S_i|)*10.$

IV. 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**:**

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 1831 iterations or epochs, and within 543.33 seconds,

$$RR_{OHC} = \frac{I_{OHC}}{I_T} *100$$

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

whereas the running time for the generalized neural networks after training and using one forward pass was 0.013 seconds. These results were obtained using a 2.0 GHz PC with 2 GB of RAM, Windows XP OS and Matlab R2009a software. Table 2 lists the final parameters of the successfully trained neural network, whereas Fig. 5 shows the error minimization curve of the neural network during learning. 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 23 images from Test Set 1.

$$RA_{OHC} = 1- \frac{(|S_p - S_i|)*10}{S_T} *100$$

that were not presented to the network before yielded 95.65% recognition rate, where 22 out of the 23 images with known optimum compression ratios. 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 the trained neural network was also implemented using the remaining 12 images with unknown optimum compression ratios from the testing set. The results of this application are demonstrated Fig. 6 which shows examples of the optimally compressed radiographs as determined by the trained neural network.

Table 1. Optimum Compression Deviation and corresponding Rates.

Input neurons	4096
Hidden neurons	50
Output neurons	9
Learning coefficient	0.005
Momentum rate	0.40
Minimum error	0.005
Iterations	1831
Training time (seconds)	543.33
Run time (seconds)	0.013

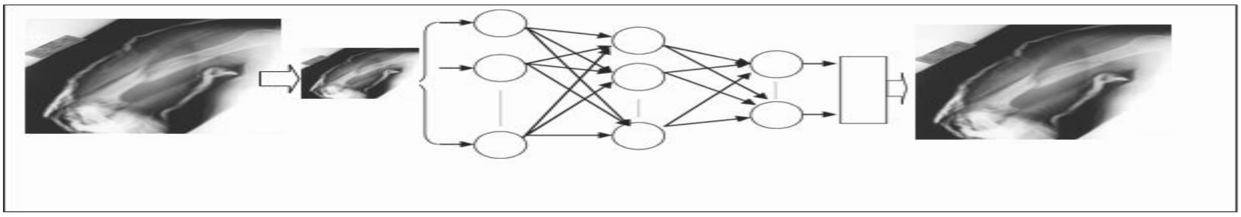


Table 2. Trained neural network final parameters.

	Accuracy Rate	Recognition
0	100 %	13/23 (56.52 %)
1	89 %	22/23 (95.65 %)
2	78 %	23/23 (100 %)

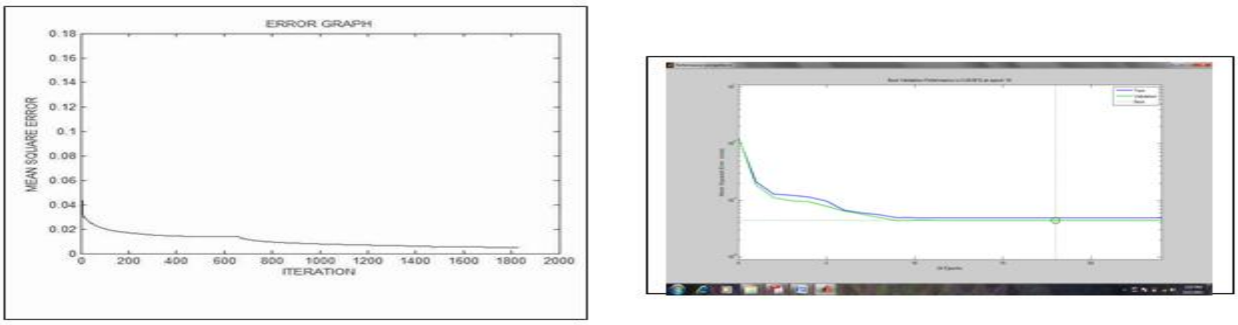


Fig. 5 – Neural Network Learning Curve.

V. Conclusions

A novel method to medical radiograph 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 haar 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 60 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 learnt to associate the 25 training x-ray images with their predetermined optimum compression ratios within 543.33 seconds. Once trained, the neural network could recognize the optimum compression ratio of an x-ray image within 0.013 seconds. In this work, a minimum accuracy level of 89% was considered as acceptable. Using this accuracy level, the neural network yielded 95.65% 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 networks. Future work will include the implementation of this method using biorthogonal wavelet transform compression and comparing its performance with Haar-based radiograph compression.

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