GRAYSCALE MEDICAL IMAGE COMPRESSION USING FEEDFORWARD NEURAL NETWORKS

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Abstract

In this paper, feedforward neural network train with backpropagation algorithm is propose to compress grayscale medical images. In this new method, a three hidden layer feedforward network (FFN) is applied directly as the main compression algorithm to compress an MRI image. After training with sufficient sample images, the compression process will be carried out on the target image. The coupling weights and activation values of each neuron in the hidden layer will be stored after training. Compression is then achieved by using smaller number of hidden neurons as compared to the number of image pixels due to lesser information being stored. Experimental results show that the FFN is able to achieve comparable compression ratio of 1:36 at PSNR 35.89 dB as compared to JPEG2000 with compression ratio of 1:20 at PSNR 40 dB.

Keywords: *Artificial intelligence, lossless compression, medical image compression, neural network.*

I. INTRODUCTION

In the past three decades, there has been a sturdy growth in the medical imaging field with various new medical image formation methods in digital format being devised. These improved imaging techniques not only able to produce medical images of higher quality with more detailed representation as compared to conventional methods but also improve the diagnostic efficiency. However, good image quality will more often than not produces a picture with larger file size [1].

This file size of medical images increases as the resolution demand increases and eventually issues may arise during transmission and communication where network resource is a constraint. Besides that, archiving these for post processing or medical act legal requirements will be a daunting task because of the large file size [2].

Both archiving and image communication services are two of the major components of a general telemedicine system where medical image file size usually poses a serious threat to the overall operating efficiency of these components. For instance, an MRI image developed with a resolution of 480 X 640 pixel and encoded in 12 bits would have a image size of 0.4608 Mbytes while a set of 24 MRI image with the same resolution would have a size of 11.06 Mbytes. Without any compression being applied, the time needed to send a single MRI image over a 56 kbaud modem would be around 65.83 seconds and 3.69 seconds on a T1 carrier system. However, when the number of images being communicates between two different locations over a network increases the total image size will grow and this in return will affect the transmission time. Based on the previous example, a set of 24 MRI images will take 27.82 minutes or 88.48 seconds on a 56 kbits modem and T1 carrier system respectively.

Hence, in order to improve the performance of the communication or storage system, the application of some sort of compression algorithm to medical images is inevitable [3]. Basically, all contemporary image compression algorithms can be classified into two main groups that are lossless and lossy methods. Lossless compression technique reproduces exact replica of the original image. In this method, compression is achieved by decorrelating neighboring pixels and then reducing the components which is insensitive to human psychovisual system. In contrary, the lossy method where compression is achieve by first transforming and representing the data in another domain before reducing components that the human visual perception is insensitive to. Both methods are filed in the Digital Imaging and Communications in Medicine (DICOM) which is one of the most widely adopted standards in the healthcare sector. DICOM is the successor of to the American College of Radiology (ARC) and National Electrical Manufacturers Association (NEMA) with established players as committee members from both the academia and industry sectors such as Siemens Medical Solutions USA Inc, Sony Europe, GE Healthcare, FujiFilm Medical Systems USA and many more. The aim of this standard is to meet specific demands related to any medical modalities that concerns about imagery and ensures the interoperability between medical imaging equipments developed by different manufacturers. The current version is 3.0 and is published in 1993 with WG-04 (work group) on compression.

Medical image compression is described in section 5 (encoding) of the DICOM standard. Among the compression algorithms recommended here are the JPEG, JPEG2000 and JPEG-LS. In JPEG, both the lossy and lossless modes are outline with the notable difference between these two is the application of Discrete Cosine Transform (DCT) together with a quantization matrix for lossy compression while the use of Differential Pulse Code Modulation (DPCM) before data encoding for lossless method. JPEG2000 is yet another recommended compression scheme by DICOM that uses Discrete Wavelet Transform (DWT) and multi component transforms. Both lossy and lossless forms are supported by JPEG2000 depending on the type of DWT and multi component transforms being used [4]. The main distinguishing feature between these two transforms is the implementation part where irreversible transform (lossy) will be done in floating point and consequently introduces round off error (quantization) while reversible transform (lossless) will be in integer form. JPEG-LS which is also documented in the DICOM compression standard, is a scheme based on the Loco-I algorithm that is capable to provide near to lossless image quality with compression ratio that outperforms lossless JPEG.

In this paper, a multilayer feedforward neural network (FFN) is proposed to compress medical images which can yield compression ratio that is comparable to a lossy algorithm and at the same time without compromising image quality. Hence, the aim of this new compression scheme is to combine the advantage of a lossy algorithm which is having small compression ratio with the image quality obtained by lossy algorithm. In this new technique a multilayer FFN is use to approximate the function represented by the image instead of extracting frequency components from the image using either fourier or wavelet transform as in the renown JPEG and JPEG2000 algorithm. The process of tuning the network according to the function represented by the image or also known as network training can be considered accomplished when the control parameter of choice that is the mean square error (MSE) has reached the predefined level. Finally, the weights of the trained neural network will be stored (in an archive system) or transferred (in a communication system). At the decompression stage, the FFN will be reconstructed using the stored weights and image pixel values can then be reconstructed. In this case, the decompressed image quality is measure using the peak signal to noise ratio (PSNR) which is computed by finding the ratio between the biggest pixel values in the image to the average square difference between corresponding pixels of the decompressed and original image. Meanwhile, the compression ratio is simply the ratio of file size between the original and compressed image.

II. METHODOLOGY

In this work, a hierarchical neural network as depicted in Figure 1 is use to compress the MRI image of a knee shown in Figure 2. This network has three hidden layers with each nodes using linear activation function. While the inner hidden layer takes advantage of the interpixel redundancy within each block, the outer layer exploits the interblock redundancy to achieve the most efficient representation of the image. The training method employed here is the backpropagation algorithm using scaled conjugate gradient for faster convergence.

In preparing the training sets, the image will first be divided into N smaller blocks of k X k pixels subimages and these blocks will be used as the training inputs. The reason to divide the image into smaller block size is to allow the computation to be done faster. Matlab will be used in this work to train FFNs with a sample image to train the network. Training starts by feeding the network with the sample image pixel values and the network weights are tune according to the backpropagation algorithm. This algorithm tunes the weights according to the error generated at the output as compare to the desired output and this alteration will carry on until the error is propagated back to the first layer. Although there are two ways the weights can be changes which are the batch and incremental, but the batch method (train function in Matlab) is applied here due to significant faster convergent time and smaller calculation error.

As for the activation function of neuron, non-linear sigmoid function is chosen over the more common hyperbolic tangent sigmoid due to consistency of the former function with the nature of the data which is between 0 and 1. Two termination criteria have been set for the training which is first the number of epochs which in this case is set to 1500 and the second parameter is the network mean square error. The training will stop and deem to be completed if either of the above the rules set above are met. After training, the MRI image is compressed by the network and the coefficients of the principal components which is the activation value obtained will be stored.

In the decompress stage the image can then be reconstructed by first recreating the FFN with the correct configuration and weights. Then, simply by feeding the corresponding activation values of each block, the relative pixel values can be computed by the network. The effectiveness of this new algorithm is gauge using two parameters which are the PSNR for accessing the quality of the decompressed image and the image compression ratio as illustrated in equation (1) and (2) below. As a comparison, the performance of this algorithm is compared to the JPEG 2000 and JPEG-LS algorithm. From [5], the PSNR of JPEG 2000 at compression ratio of 0.08 bpp (1:100) and 0.4 bpp (1:20) is around 40 to 60 dB while this figure increase substantially at lower compression ratio of 0.8 bpp (1:10) at around 90 to 100 dB. Moving on to the JPEG-LS technique which is lossless hence only the compression ratio will be referred. From [6], the compression ratio provided this type of compression ratio is 1:3 to 1:5.

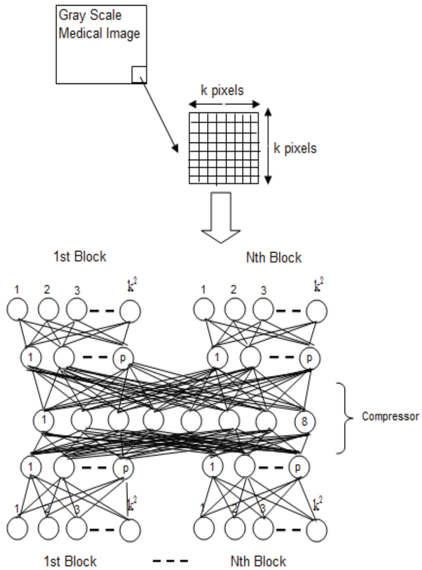

Figure 1: Three Hidden Layer FFN Medical Image Compression Algorithm

Figure 2: A Reference MRI Image of a Knee

$$MSE = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} \left[I(x,y) - I'(x,y) \right]^2 \qquad (1)$$

Where,

I(x,y) – original image
I′(x,y) – decompressed image
M, N – dimension of the image

$$\text{Compression Ratio} = \frac{\text{Compressed Image File Size}}{\text{Uncompressed Image File Size}} \qquad (2)$$

III. RESULTS AND DISCUSSION

A magnetic resonance image is compressed using the new FFN compression scheme. Different configurations have been made to the network including changing the number of neurons in the compressor level and modifying the subimage block dimensions. Both the compression ratio and PSNR of the reconstructed image were observed and deliberately analyzed. The results of the experiment are tabulated in table 1. As a comparison, the compression performance of JPEG2000 in compressing the same image is tabulated in table 2.

A careful study on the results of these two methods reveals that FFN compression scheme is able to achieve compression ratio very near or at times better than JPEG2000 without compromising the image quality. Similarly, both methods produce images of lower quality at higher compression ratio.

The compression results of FFN show that the more number of neuron used in the compressor level the better quality of the decompressed image. Basically, a network with 16 compressor neurons compressed using an 8 by 8 pixel block will produce an image with a decent PSNR of 37.35 dB as compared to a network with 4 compressor neurons compressed with the same subimage dimension can only manage achieve PSNR of 17.56 dB. This shows that the image will be better approximated with more neurons which represent the principal components being generated. However, the PSNR obtained using a network with 8 and 16 compressor neurons doesn't change much as the optimized number of principal components to sufficiently represent the image may have been reached.

Moving on to the number of compressor nodes, the PSNR is found to be inversely proportional to the image block size and compression ratio. For instance, a network 16 compressor neurons gives a compression ratio of 1: 30 when a 4

X 4 block is use and this increases to 1:36 when a bigger block size of 16 X 16 is utilized. On the contrary, the PSNR decreases from 39.56 dB to 35.89 dB which indicates a reduction in the image quality. This is expected because a bigger block size contains more information and this provides greater opportunity to discover and dispose redundant information which is the reason for getting bigger compression ratio. However, these compromises the PSNR as bigger MSE will be produced due to larger variations between each block.

Table 1: Compression Performance with Different Number of Compressor Nodes and Subimage Dimension

Number of Compressor Neurons	Subimage Dimension	Compression Ratio	PSNR (dB)
4	4 X 4	1:50	17.56
	8 X 8	1:60	16.42
	16 X 16	1:75	13.22
8	4 X 4	1:45	26.32
	8 X 8	1:48	24.33
	16 X 16	1:51	23.76
12	4 X 4	1:35	34.83
	8 X 8	1:39	33.89
	16 X 16	1:47	32.02
16	4 X 4	1:30	39.56
	8 X 8	1:35	37.35
	16 X 16	1:36	35.89

Table 2: Compression Performance of lossy JPEG200 for Various CR

Compression Ratio	PSNR (dB)
1:70	15.56
1:60	18.02
1:40	32.22
1:30	37.32

In this paper, FFN is proposed to compress medical images. The performance or effectiveness of the new proposed algorithm is evaluated with different number of compressor nodes and subimage block size. Thereafter, the compression ratio and PSNR are analyzed. The new proposed algorithm has a comparable compression ratio of 1:30 to JPEG2000 of 1:20 with a decent PSNR of 39.56 dB for the former and 60 dB for the latter. Results show that the compression performance parameters which are the compression ratio and PSNR is affected design of the compressor level and size of image block. In brief, the PSNR is inversely proportional to the subimage block size and compression ratio but is directly proportional to the number of neurons used.

Even though the compression ratio of this new algorithm is not far superior compare to lossy JPEG2000 or other lossless JPEG methods in terms of the image quality and compression ratio, but then based on the promising results obtained the FFN holds great potential in the medical image compression field due to the powerful parallel computational capability of ANN. There is still plenty of room for improvement as the optimum ANN network architecture and configuration to compress grayscale medical images has yet to be found.

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