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Medical images Compression using convolutional neural network with LWT

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***Abstract*— In compression of medical image using convolutional neural network trained with the back-propagation algorithm and lefted wavelet transformation is proposed to compress high quality medical images. It gives much better result as compared to feed-forward neural network . Medical image processing process is one of the most important section of research in medical applications in digital medical information. In this new approach , a three hidden layer convolutional neural network (CNN) is applied directly as the main compression algorithm to compress an MRI, X-ray, computer tomography images. 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 achieved by using smaller number of hidden neurons as compare to the number of image pixels due to lesser information being stored. experimental results proves that the anticipated algorithm is superior to another algorithm in both lossy and lossless compression for all medical images tested Experimental results show that the CNN is able to achieve comparable compression performance to popular existing medical image compression schemes such as JPEG2000 and JPEG-LS.**

The Wavelet-SPIHT algorithm provides PSNR very important values for MRI and CT scan images.

***Index Terms*— Artificial intelligence, convolutional neural network, medical image compression, lossless compression, lossy compression, Lefted Wavelet Transformation, JPEG, lossless JPEG.**

I. INTRODUCTION

In the past three decades, medical image processing process is one of the most important areas of research in medical applications in digitized medical information. 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 in the medical sector. Among the medical imaging methods that are advancing rapidly are computer tomography scan and mammography that uses X-ray (radiology) and single photon emission tomography (SPECT) and positron emission tomography (PET) which uses either low or high energy gamma ray (nuclear medicine). For this reason, this paper is decomposed into three parts: the first part will present a representation of the Lifting scheme, then the second part present in the biorthgonal wavelet (WT) CDF 9/7 and finally this paper present a SPIHT algorithm for medical image coding. In order to evaluate medical image compression by our algorithm, The PSNR results obtained are compared with the existing techniques namely JPEG codec [6]. However, this better image quality acquired by these technologies driven imaging methods is compromise by a larger file size than those obtained traditional medical image modalities [1]. In 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].

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 either lossless or lossy methods. Lossless compression technique also known as reversible transform is due to the fact that the decompressed image is an exact replica of the original image.

In this image compression method, compression is achieved by de-correlating neighboring pixels and then encoding this information with a variable length encoder with in process. In 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. Among the compression algorithms recommended here are the JPEG, JPEG2000 and JPEG-LS. In JPEG,JPEG2000 both the lossy and lossless modes are outline with the notable difference between these two is the application of lefting based Discrete Cosine Transform (DCT) together with the corresponding quantization matrix. Both lossy and lossless forms are supported by JPEG2000 depending on the type of LWT and multi-component transforms being used [4].

In this approach, a multilayer convolutional neural network (FFN) is proposed to compress medical images which can yield compression ratio similar to lossy methods while not compromising good image quality. In this new technique a multilayer CNN is use to approximate any arbitrary function represented by an image. The process of tuning the network according to the function represented by the image also known as network training will be carried out until the mean square error (MSE) and (PSNR) has reached the desired level.

Finally, the weights of the trained neural network will be used in the compression stage to extract out the principal components of the image. These values which represent the reduced data of the original image will first be quantized accordingly and then stored and thus compression of the

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original image has been achieved. At the decompression stage, image pixel values can be recalculated by using the stored weights and principal components. In this case, the decompressed image quality is measured 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.

II. GENERAL IMAGE COMPRESSION ALGORITHMS

All contemporary lossy image compression methods can be segmented into three fundamental steps which are removing image redundancies, quantization and coding as shown in figure 1 [5]. Concisely, the aim of this first part of the algorithm is to achieve the most effective representation of the image pixels in another domain that would facilitate the operation of the next stage by exploiting the inter pixel redundancies in the image. Popular methods that are used to accomplish this step includes orthogonal transforms such as lifting based Discrete Cosine Transform (DCT) and Wavelet Transforms (WT) for lossy and Differential Pulse Code Modulation (DPCM) for lossless. In this stage, there is no compression that takes place and the transformed image is still the exact representation of the original image.

Thereafter, in the quantization step, some of the transformed coefficients will be discarded or round up according to certain predefined rules which are normally devised by exploiting the limitation of human visual perception system. For instance, in JPEG, the spatial frequency components obtained through the DCT will be multiplied with a predetermined quantization matrix (in the JPEG standard) that will concentrate low spatial frequency components at the top left corner of the block while suppressing most of the high frequency components at the bottom right corner to zero. This quantization matrix is devised by exploiting the fact that human perception is more sensitive to low spatial frequency components change over a considerable large area rather than the variation of high spatial frequency components. Thus, through this step, not only loss of information from the original signal is introduced and some form of compression is achieved but at the same time will facilitate further compression at the coding process.

Finally, building on Shannon's entropy coding concept, lesser bits can be used to represent redundant information and vice versa on the quantized coefficients based on a variety of established techniques developed in the information theory. For example, after scanning through the image in a "zigzag" fashion, JPEG uses Huffman or arithmetic coding with the latter being rarely implemented due to costing issue (covered by license) [6, 7].

As pointed out by [8], the critical factors in an image coding algorithm would be the quantization and the information encoding section. Hence, the authors recommended that efforts should not be spent only in optimizing the spectral transformations of image as there is only a mere 1 dB peak signal to noise ratio (PSNR) difference between the popular LWT and DCT transforms. In fact, both the quantization and entropy encoding area has been an active area of research in recent years.

Many effective algorithms that have been devised such as the Embedded Block Coding with Optimized Truncation (EBCOT) implemented in the JPEG2000 standard, embedded Zero Tree Wavelet (EZW) [9] and set partitioning in hierarchical tree (SPIHT) which provides decent compression ratio.

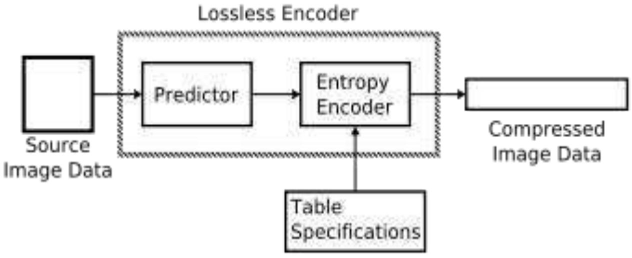

Figure 1: Functional block of a lossless image compression algorithm

III. NEURAL NETWORKS IN IMAGE COMPRESSION

In this method, there are also other work done which use artificial intelligence (AI) such as convolutional neural network, genetic algorithms (GA) and artificial neural networks (ANN) to compress images [10, 11].

These techniques prove viable with findings being reported that image compressed by ANN is very competitive in terms of the compression ratio and decompressed image quality and even outperform traditional algorithms under certain conditions [13]. The development of neural networks in the field of image compression can be done in the direction of any of these three methods [14].

The first method applies multilayer ANN directly as the compression engine which is similar to performing a Karhunen-Loeve transform to the image data and obtaining an optimized representation using elements that are responsible for most of the variation in the image data which is in contrast to the fixed orthogonal basis function use in Fourier series (sinusoids). In this method, compression is achieved by reducing the dimension of the original image data during the training phase by mapping the input neurons (equals to the number of pixels under consideration) to a hidden layer with lesser number of neurons.

This is addressed in figure 2 below. After training, when the network converges to the desired network performance parameter, the corresponding output weights will be stored. During compression, the coupling weights will remain the same throughout the process and the obtained activation values (coefficients of the orthogonal basis function in the new vector space) of the hidden layer will be kept as the compressed image file. Later in the decompression stage, the image can be rebuilt by using the activation values and coupling weights.

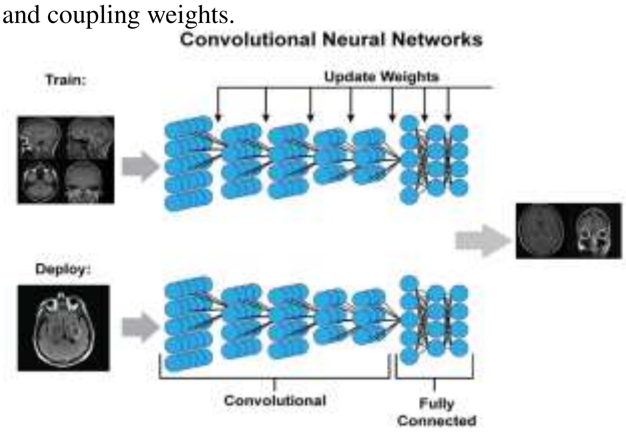

Figure 2: Direct Application of Convolutional Neural Network to Compress Images

In the second method, existing compression algorithms are implemented by a single neural network just by tweaking the network learning algorithm to suit the intended task. For instance, wavelet neural networks [15] are designed to decompose the signal in hand into the optimized linear combination of weighted daughters of a mother wavelet using multilayer CNN.

In this case, the activation value is the daughter wavelet while the related weights would be the optimized coefficient value. On the contrary to the conventional method faces the difficulty of finding the best wavelets to decompose the image in a separate in an independent stage, the neural network implementation offers a much efficient way by incorporating the search into the wavelet decomposition stage directly. Other current compression technologies that is successfully implemented using ANNs includes fractal compression [11] which is based on the fact that "self similarities" are often found within an image and predictive coding for lossless compression. Lastly, the application of ANN to image compression had also been done indirectly by playing supporting roles to conventional compression methods.

Basically, in this context, neural networks would only be used to preprocess the image data so that traditional compression scheme can achieve better compression performance. Although the participation of neural network in this type of compression is not that straightforward., but base on the capability of ANN in extracting critical features in a data which is much established, the development of such algorithms that can harvest the strength of ANN and to improve the performance of current compression methods show great opportunity.

IV. 3METHODOLOGY

In this compression process , a hierarchical neural network as depicted in Figure 2is use to compress the (CT)image of a brain shown in Figure 3. This network has three hidden layers with the nodes in each layer using linear activation function. While the inner hidden layer takes advantage of the inter-pixel redundancy within each block, the outer layer exploits the inter block redundancy to achieve the most efficient representation of the image.

The training method employed here is the back-propagation 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 for dividing the image of interest into smaller block size is to reduce the computational time. 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 back-propagation 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 changed that 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 (CT) 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 CNN 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 [16], 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 [17], the compression ratio provided this type of compression ratio is 1:3 to 1:5.

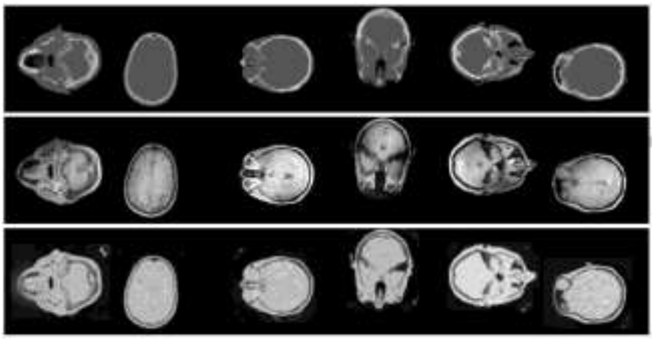

Figure 3: A Reference CT Scan Image of a brain

$$MSE = \frac{1}{NxM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[X(i,j)-Y(i,j)]^2$$

where,

a) I(x,y) is the original image
b) I'(x,y) is the decompressed image
c) M, N is the dimension of the image

V. RESULTS AND DISCUSSION

Medical image is compressed using the CNN compression with lefted wavelet transform 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 analyzed. The output of the experiment are tabulated in Table 1. The results show that the more number of neurons 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 34.72 dB as compared to a network with 4 compressor neurons compressed with the same subimage dimension can only manage achieve PSNR of 17.41 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 16 and 32 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: 35 when a 4-by-4 block is use and this increases to 1:35 when a bigger block size of 16-by-16 is utilized. On the contrary, the PSNR decreases from 34.72 dB to 35.69 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.

Number of compressor neurons	Subimage Dimension	Compression Ratio	PSNR(db)
4	4x4	1:52	18.66
	8x8	1:61	17.41
	16x16	1:72	14.32
8	4x4	1:45	27.35
	8x8	1:49	25.44
	16x16	1:52	24.77
16	4x4	1:35	35.89
	8x8	1:39	34.72
	16x16	1:48	35.69
32	4x4	1:32	40.56
	8x8	1:35	37.89
	16x16	1:37	35.69

Table 1: Compression with Different Number of Compressor Nodes, Subimage Dimension and get PSNR(db)

VI. CONCLUSIONS

In this image compression approach, CNN is proposed to compress medical images with the help of lefted wavelet transform. The performance or effectiveness of the new proposed algorithm is calculated with different number of compressor nodes and subimage block size. Thereafter, the compression ratio and PSNR are evaluated. The new proposed algorithm has a comparable compression ratio of 1:30 to JPEG2000 of 1:20 with a decent PSNR of 39.59 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. So, the PSNR is inversely proportional to the subimage block size and compression ratio but is directly proportional to the number of neurons taken. Even though the compression ratio of this new algorithm is still inferior compare to lossless JPEG JPEG2000 or other JPEG2000 methods in terms of the image quality and compression ratio, but then based on the promising results obtained the CNN holds great potential in the medical image compression field due to the powerful parallel computational capability of ANN.

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