Applied Medical Informatics
Original Research Vol. 41, No. 1 /2019, pp: 33-39

A comprehensive intelligent compression method on DICOM images

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Received: December 21, 2018/Accepted: March 29, 2019/ Published online: March 31, 2019

Abstract
Virtual medical imaging has overgrown in recent years and later implemented in such situations - all of the radiological modalities which include Computed tomography (CT scanners), Magnetic resonance imaging (MRI), ultrasound (US), positron emission tomography (PET), X-Ray (radiographs) made employing more than one providers and hosted by one or many websites which communicated over the DICOM network. The DICOM images required huge hard disk space and excellent transfer speed, which need to compress the DICOM images for effective capacity and transmission over the internet. The compression process is applied through utilized a recurrent neural network algorithm establishing Trainscg as the activation function. Extraordinary high-quality metrics like mean squared error (MSE), Peak signal-to-noise ratio (PSNR), Compression ratio (CR), and Compression time are computed on several medical test images. The proposed compression method shows better experimental results than the existing techniques based on performance parameters except for the compression time for the large image only.

Keywords: DICOM (Digital Imaging and Communication in medicine); Image Compression; Recurrent Neural Network

Introduction

Medical imaging is a branch of a digital image that revolutionized healthcare production in the past period, allowing medical experts to identify, analyze, and treat diseases. DICOM (Digital Imaging and Communication in Medicine) is the international standard for transmitting, storing, retrieving, printing, and displaying medical imaging information. Magnetic Resonance Imaging (MRI), Computed Tomography (CT scan), Positron Emission Tomography (PET), radiography, and ultrasonography are resources for medical images [1-3].

Many medical centers are produced a large number of medical images that required huge space storage, which cannot be transmitted with high speed over the telemedicine network for medical expert [4].

The technological development in the field of medical images leads to the necessity to increase the possibilities of storage. To assure proper storage and timely sharing of medical images, the compression methods must assure high quality. Image compression is a step of changing over the digital image in ranges to decrease the bit's number required to shrink the capacity space and the transport cost while maintaining the reasonable quality of compressed image [5].

The field of image compression is a standout amongst the most required and vest in the research area. Compression does not only mean reducing the size of data with low reduction of stored data but also reconstructing the original data. The diagnosis and analysis of medical image are applying satisfactory when lossless compression is used, that keep all main image information required for storage and transmission. Opposite, the lossy compression, do not guarantee to keep the information in the necessary features with more saving space [6-8].

Artificial neural network techniques are using in the field of image compression for several reasons, including the ability to deal with noisy and incomplete data more than traditional methods, in addition to pre-treatment of input patterns to produce simpler patterns with fewer components. The complete information obtained from the external environment (compressed data stored) gives better compression rates at better protection levels. Neural networks are the best tools to deal with image data because of the adaptation feature. The use of neural networks in the image compression area accomplishing good results [9-11].

Feedforward neural network with multilayer is a well-known model that depends on back propagation algorithm as training function have some weaknesses, for example, local minima, and overfitting problem, and to solve those complications we could utilize the recurrent neural network to accelerate the learning process and improved the network performance [12].

Recurrent Neural Network (RNN) has a critical feature which is one feedback connection at least; therefore the activations can be moved in a loop, which enables to establish sequential processing, learning sequences, sequence recognition, sequential association, and prediction process for the network [13].

The Trainscg activation function with the recurrent neural network is used to update both weight and bias values which considered virtual annealing network. A network which remembers previous inputs or feedbacks previous outputs may have greater success in the compression process [14,15].

The goal of the present research was to use new intelligent systems as recurrent neural networks in compressing a medical image based on multi-layers (one input layer, two hidden layers, one output layer) to get better results.

Related Work

A mix between discrete wavelet transform and multilayer feedforward neural network was introduced in [16] as image compression techniques. The combined methods are used for enhanced results and solved many drawbacks in many other algorithms. The compression time is low, the best of the reconstructed image is excessive, with constant bit-rate.

A feedforward neural network with one-layer is used as image compression in [17]. The little neuron in hidden layer act as stock for the compact features of the image, with [256 240 256] where 256 corresponds to the number of nodes in the input, and 240 corresponds to the no. of nodes in the hidden layer as network architecture. Many parameters are used to analyze the model such as No. of Epochs, Hidden Layer Nodes, Momentum Constant, and No. of Iterations to recognize the superior performance. The system has a highly compressed process and a decent quality image.

In [18] the mixture of Bipolar Coding and LM technique based on an artificial neural network are applied for image compression application. The Bipolar coding network is trained on a small block of the image with updated both of the weights and the biases in each step which need more time and space, to overcome this issue the mathematical Levenberg-Marquardt algorithm is utilized. The LM model is suitable for small and large image compression.

Fractal united with backpropagation neural network algorithms for image compression in [19]. The neural network used as tools for reducing the search space done by a fractal process which divided the brain MRI Image into ranges. The model reduced the compression time, so the performance is improved without debasing the image quality.

In [20] an adapted back-propagation model for medical image compression was implemented. The image converted then normalized then divided into blocks that transformed into a vector of N-dimensional before the training step proceed, however, the weights started randomly then a new weight is created and adjusted depends on the quality of the reconstructed image. According to the execution of the model, it fits for real-time usage.

Recurrent Neural Network

RNN is organizing with one or more input association that passes the neuron layer output to the preceding layer(s). RNN is fully connected for all neurons, so the network connection becomes dynamic, as a state memory [21].

The recurrent neural network contains one hidden layer with feedback connections that act as a smart implementation for compressing the medical image. The network consists of 3 layers, including input, hidden, and output layers through a connection of feedback type [22].

The (jth) hidden layer value is calculated based on the sum of all I network input vector x and their weight v for the learning model (nth) as shown in Equation (1) [23]:

$$net_j(n) = \sum_{i=1}^{I} v_{ji} x_i\,(n), \quad j = 1, \ldots \ldots \ldots ., J. \tag{1}$$

The achieved sum can be written within the shape of an impulse transfer function as shown in Equation (2) [23]:

$$G_j(z) = \frac{B_j(z)}{A_j(z)} = \frac{\ddot{y}_j(z)}{net_j(z)} = \frac{b_{0j} + b_{1j} z^{-1} + b_{2j} z^{-2}}{1 + a_{1j} z^{-1} + a_2 z^{-2}} \tag{2}$$

where a, and b are the filter coefficients.

The jth hidden layer output (Dynamic Elementary Processor (DEP unit)) is shown in Equation (3) [23]:

$$y_i(n) = e^{-\frac{1}{2}(\frac{\ddot{y}_i(n) - t_j}{\sigma_j})2} \tag{3}$$

where t_j is the center and σj is the width of the activation function, and the outputs are calculated, and all network constraints are got to be adjusted in the learning process.

The recurrent networks can have a limitless memory considering time as well as the instant input space. Recurrent networks are formal in many applications such as nonlinear time series prediction, system identification, and pattern classification [24], as well as RNNs, may have better learning and performance in a shorter time than feedforward networks, which can be used in compression field.

The Proposed Algorithm

The model using a 4-layer recurrent neural network, one input layer (X), two hidden layers (H1, H2), and one output layer (Y), which characterized by determined weight matrix wn.

The training is done through the recurrent neural network, the image can be efficiently encoded using the determined selected weights Wn matrix for encoding, and W_h matrix for decoded, through many steps:

Step1: Read the medical test image
Step2: Divide the 128 *128 image into 8 blocks pixels
Step3: Reshape the image blocks before the training phase
Step4: Initialize the recurrent neural network neurons
Step5: Apply scanned vectors to each neuron on the input layer
Step6: Determine the weight value $W_{x\ h}$
Step7: Perform the (Trainscg) function based on the initial weights
Step8: Sends the results of the previous layer to the next layer
Step9: Step 6 and 7 are repeated
Step10: Gather the outputs data together

Step11: Train the recurrent neural network to get best compression result and remain the weights (store the new weight value)

Step12: Reshape the output matrix.

The process of decompression is a matching process of the compression process on the Receivers side.

The procedure of the proposed model is shown in Figure 1.

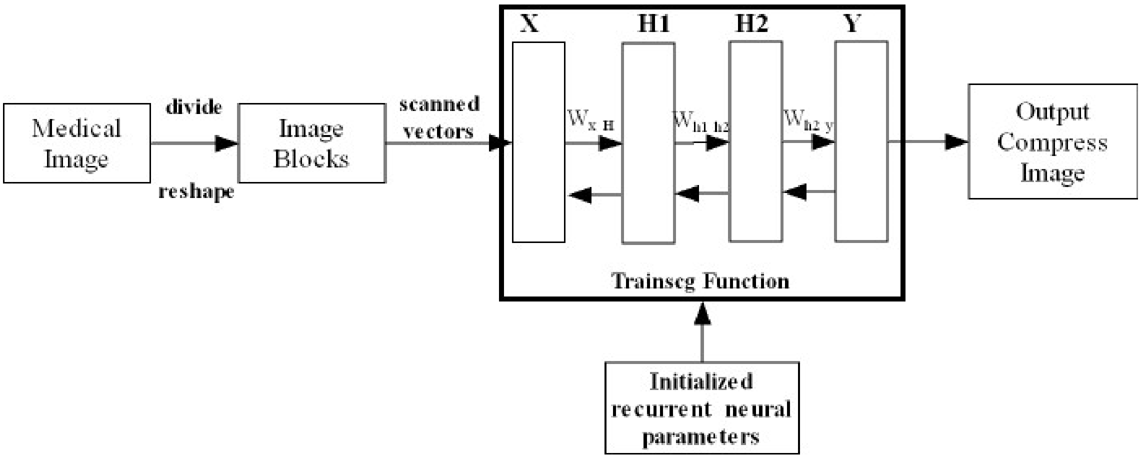

Figure 1. Block diagram of The Compression model

Algorithm Implementation

The analysis has been done on Core I5 -1.7 GHz CPU with 4 GB RAM running on Windows 10 pro and using MATLAB 2017a. Results experiment on two standard medical image, which is Brain – MRI (461 KB) and head-MRI (82KB) collect form kaggle dataset website [25], based on various quality metrics such as MSE, PSNR, Compression Ration, and Compression Time. The images are 128×128 dimensions with 8-bit grayscale and used for both intelligent methods (Recurrent and Feed Forward)

Mean Square Error

The mean square error (MSE) is used to calculate the error between the original image and the reconstructed image, as shown in equation 4:

$$MSE = \frac{1}{MN}\sum_{i=1}^{N}\sum_{i=1}^{M}[C(i,j) - C'(i,j)]^2 \tag{4}$$

where M and N are the numbers of rows and columns in the input image matrix, C(i,j) denoted to the original image, while C' (i,j) denoted to the reconstructed image. When the MSE value is low, then the error between the two images is small.

Peak Signal to Noise Ratio (PSNR)

The Peak Signal to Noise Ratio (PSNR) is used to estimate the compression model, as shown in equation 5:

$$PSNR = 10 \times log_{10}\left[\frac{Max^2}{MSE}\right] \tag{5}$$

Theoretically, the PSNR value is between 30 and 50 dB for lossy image compression, and when the value of PSNR is greater than 40 dB, then The differences between the images are tiny.

Compression Ratio

Compression Ratio (CR) was calculated as shown in equation 6:

$$CR = N1 / N2 \tag{6}$$

where N1 is the number of compressed image bits, and N2 is the number of original image bits. The higher the CR, the lower the disk scape.

Results and Discussion

The comparison between the image compressions methods has been introduced in Table 1. A comparison is based on image quality measurement MSE, PSNR, and CR values which have been used to estimate the quality of the reconstructed image and the computation time of running compression process.

Table 1. The quality measurement for two intelligent methods

Method	Image	MSE	PSNR(dB)	CR	Time(Sec)
Recurrent	Brain	0.9715	43.4853	1.6698	19.309701
	Head	1.4380	41.7819	0.9950	27.625376
Feed Forward	Brain	2.1532	34.3088	0.9349	16.454589
	Head	2.7358	31.9496	0.9739	11.613273

MSE = Mean Squared Error; PSNR(dB) = Peak Signal-to-Noise Ratio; CR = Compression Ratio

The original and decompressed images are presented in Figure 2. The error versus epochs of the recurrent neural network is shown in Figure 3.

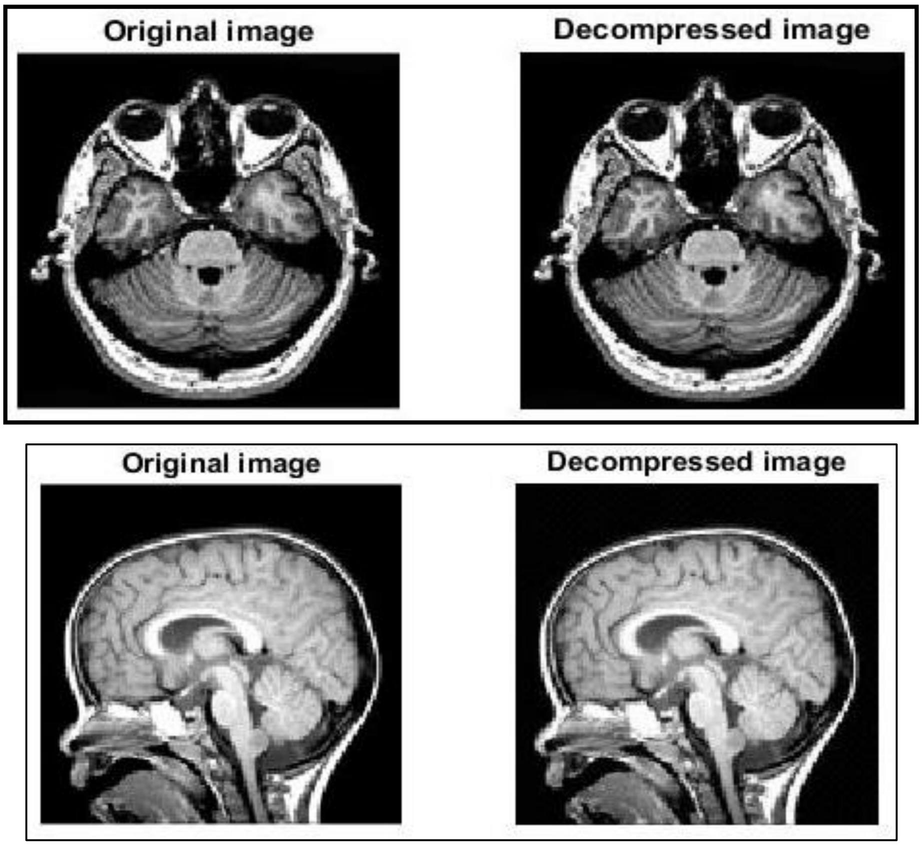

Figure 2. The original and decompressed image

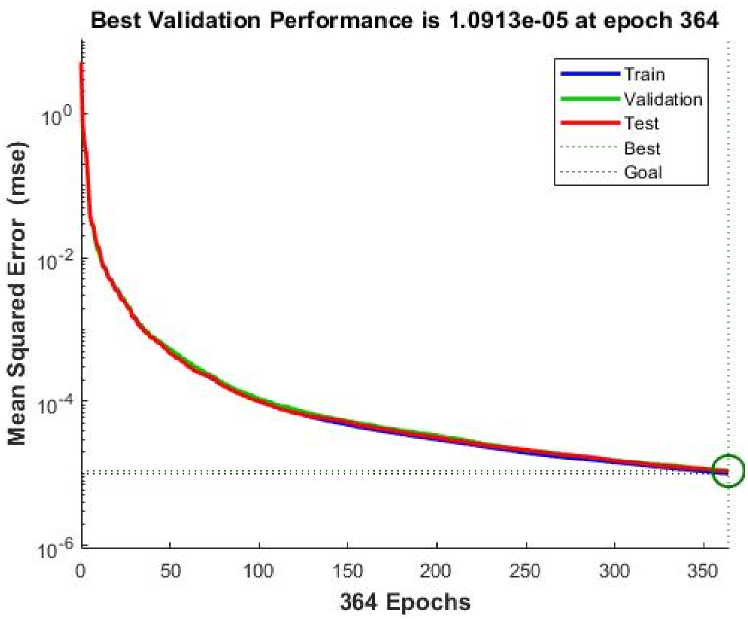

Figure 3. Error versus Epochs for the proposed model

The reported results show that the recurrent neural network algorithm gives better results than Feed Forward neural network algorithm in MSE (lower error), PSNR (higher value), Compression Ratio (higher ratio), especially at brain image that have larger size. While the time needed to compress the image was better in Feed Forward neural network than in the recurrent neural network, because the feedback connection step which increased the compression time.

From previous results, the reconstructed image becomes of better quality in recurrent than Feed Forward neural network for the high PSNR value and the feedback connection step, which positively effects on the MSE Error which decreased significantly. With the possibility of searching in the future for a solution to reduce the time taken in the compression process.

Image compression is the foremost vital applications in digital image processing these days. The medical image has extensive data. For this reason, the medical image got to be compressed before transmission and storage, as the limitation of storage capacity and bandwidth. Recurrent training neural network model is proposed for compressing the medical image with small image blocks 8×8. A good quality medical decompress image is obtained with high PSNR and a low MSE error value, which achieved high compressed. A decent quality medical decompress image is acquired with high PSNR and low MSE value, which accomplished high compressed. The experimental results clearly indicated that the performance of the recurrent neural network is greatly improved in many measurements without reducing the image quality with the possibility of improving the algorithm and used it online in the future.

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