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Neural Network Based Image Compression Approach to Improve the Quality of Biomedical Image for Telemedicine

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Authors' contributions

This work was carried out in collaboration between all authors. Author AKJS accomplishes analysis of problem, solutions, data sets, input/output constraints; background study, designing of algorithm methodology and evaluation factors, implementation of designed algorithm, testing, evaluation and compare the results with existing JPEG2000 image compression standard. Author OAS managed the analyses of the study, designing and implementation phases. Both the authors read and approved the final manuscript.

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ABSTRACT

Aims: In Telemedicine, the use of digital utilization for medical diagnosis helps medical practitioners for better and fast treatment of patients, but at the same time it increase the storage resource requirement for archive the images as they are in high resolution and size. To minimize the size it must be compressed before transmission and stored. On the other hand, the compression will reduce the image affinity, particularly when the images are compressed at lower bit rates. The reconstructed images endure from overcrowding artifacts and the image quality will be severely besmirched under the circumstance of high compression ratios.
Methodology: To meet these defy, numerous amalgamated compression algorithms solely for medical imaging are developed in the recent years. But a need of accurate technique/s is highly essential to avoid any lethal results. Artificial intelligence (AI) techniques are highly accurate and hence preferred for automated image classification, segmentation and compression.
Conclusion: To accomplish the goal of performance enhancement with respect to compression ratios and deciphered picture quality an algorithm is developed using

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advance Artificial Neural Networks (ANN) for image compression (IC) and the results are compared with existing image compression techniques viz JPEG2000. This work is explored in the context of Magnetic Resonance (MR) image classification, segmentation and compression.

Keywords: Telemedicine; image compression; artificial intelligence; accuracy; diagnosis; performance.

1. INTRODUCTION

One of the primary benefits of digital data is that it can be compressed. Compression reduces the extent of bandwidth required to transmit information, thus decreasing the telecommunications costs. Compression of tranquil images (e.g. picture or x-ray) is also important in telehealth, particularly in teleradiology. Still image compression is categorized as lossless or lossy. Lossless compression produces no noticeable loss of image quality between the transmitting and receiving sites and is desirable for clinical images. Utmost lossless compression ratios are 3:1, although wavelet compression promises 10:1 ratios or superior. Lossy compression outcome in images at the receiver site are substandard in quality to the original. At epochs a lower quality image is still clinically good enough, particularly when enhanced transmission speed is important.

Medical Image Compression (MIC) is basic but important factor in the Telemedicine. It is required to have an adept algorithm for compression of medical imaging modalities like CT, MRI and Ultrasound for providing medical care's to patients in remote locations. In Telemedicine the broadcasting of medical images requires a high data rate so as to obtain a good quality transmission with a reasonable delay. In order to pact with the huge amount of information to be stocked and transmitted, a compression of the data, without loss of information, is usually obligatory. The key aspect in telemedicine is the availability of necessary bandwidth for transfer of images of very large sizes, resolution etc., of typical medical applications. This poses new challenge in rustic regions where bandwidth may be a limitation and low speed wireless links may be the communication channel. In such situation shrinking the data size turn out to be a possible solution which can be achieved using compression. The image transmission time relays upon the bandwidth and the data transfer speed, so for the optimal use of the channel bandwidth and the faster data transfer, it is necessary to transmit the medical image data in compressed form. Increasingly, medical images are acquired and stored digitally or various film digitizers to convert traditional medical images into digital format. These images are extremely large in size and figure, and compression proffers a means to reduce the cost of storage.

The solution is to present an inventive image compression scheme, which is especially apt for image compression over tapered network typically required for telemedicine applications for providing better health facilities to the people living in the dispersed locations of Saudi Arabia.

Image compression is evolving area in multi disciplinary applications. This field is growing exponentially, due to its widespread applications in digital imaging and transmission. Various applications need high effective image compression. In variety of applications, medical image processing is a rapidly evolving area. In case of medical image processing medical samples are transferred over a channel from one location to other for remote analysis. In such cases the observer needs accurate information as near to as the original sample to have correct decision. To achieve higher rate of accuracy large volume of data need to be transferred so that information can be retrieved accurately. However in current scenario to transmit this large volume of data, a higher resource such as high bandwidth is needed. Improving allocated bandwidth is not an economical solution; hence advanced compression approaches are to be developed so as to compress the medical samples with lowest level of errors.

For the compression of medical images various image compression approaches were proposed in past. The conventional image compression approaches such as JPEG [1], JPEG-2000 [2], SPHIT [3], EBCOT [4], Lifting scheme [5] etc. were proposed earlier. These approaches are majorly categorized under lossy or losseless compression schemes. In lossy compression [6] the information are not accurately retrieved at the receiver side resulting in low PSNR. These methods are basically suitable for faster transmission approach. In various scenarios where degradation of image is not tolerable, lossless compression schemes were proposed. Lossless compression scheme [7] is a method that allows the exact accurate original data to be reconstructed from the compressed data. A scheme such as wavelet-based compression with adaptive prediction [8] is a lossless approach of image compression. This scheme is mainly used to achieve higher compression ratio. For obtaining a lossless compression in [9] a lifting scheme is suggested based on adaptive threshold.

Lossy and lossless compression schemes were found limited while applying over medical image processing. In order to retrieve the sample with highest accuracy and faster transmission, for this reason artificial intelligence based approaches were proposed. This Artificial Neural Networks (ANN) has been applied to medical image compression problems, due to their superiority over traditional methods when dealing with noisy or incomplete data. ANN approaches are accurate in making decision but are computationally effective. Lanzarini L et al. [10] have presented a technique in medical application of images compression using neural networks, which allows to carry out both compression and decompression of the images with a fixed ratio of 8:1 and a loss of 2%. Here back propagation network is created for correspondence functional calculations of input and output patterns.

Similar approach in [11] with back propagation algorithm using Feed Forward Neural (FFN) network is suggested. In this method medical image compression is carried out by calculating coupling weights and activation values of each neuron in the hidden layer. This method found to be better in terms of PSNR compared to conventional JPEG approach. S. Anna Durai, & E. Anna Saro [12] have suggested another compression technique using back propagation method with Cumulative Distributed function (CDF). This approach is based on mapping the pixels by estimating the CDF values. However, the decompressed image is fuzzy which is not suggested in Medical applications.

To improve the retrieval accuracy, Chee Wan [13] had proposed a neural network approach based on preservation of edges. In this network, quantization levels are used to represent the compressed patterns. The average Mean square value is calculated to achieve the compression ratio. In [14], a lossless medical compression technique based on neural network with improved back propagation method is proposed. From the analysis, it is found that the system exhibits significant performance in compression with low PSNR. Khashman [15] has proposed a medical compression using a neural network in which a Haar wavelet compression with nine compression ratios and a supervised neural network that learns to associate the image intensity (pixel values) with a single optimum compression ratio. The limitation of this method is image quality is not good which is not tolerable in medical Processing applications. To improve the image quality, in [16] Neural network with multi-resolution method is suggested. This method uses a filter bank that can synthesize the signal accurately from only the reference coefficients will be well suited for low-bit rate coding where the detail coefficients are coarsely quantized. This approach shows advantages over the conventional approaches for compression at low bitrates, although its performance suffers at high bitrates. For achieving higher bit rates Jianxun & Huang [17] presents neural network concept with principal component analysis. Convergence speed is high for this technique but the image quality is poor. A similar technique is proposed in [18]. The technique includes steps to break down large images into smaller windows and to eliminate redundant information. From the analysis this technique results in achieving higher compression ratio with the cost of high complexity.

Cottrell, Munro and Zipser [19] developed a multilayered perceptron neural network with back propagation as the error learning function. This technique results in optimal compression ratio. Khashman and Dimililer [20] have presented neural network for image compression by DCT transform. Here compression is achieved by DCT coefficients and a supervised neural network that learns to associate the grey image intensity (pixel values) with a single optimum compression ratio. More recently, different image compression techniques were combined with neural network classifier for various applications [21,22,23]. However, none of these works has achieved optimum compression ratio. To get higher compression ratio, neural network with bipolar coding [24] was proposed. The Bipolar Coding technique using feed forward back propagation neural network converts decimal values into its equivalent binary code and reconvert in decompression phase. Besides higher compression ratio it also preserves the quality of the image. In [25] similar image compression technique for neural network with GA was suggested. This method mainly focuses on GA algorithm which uses XOR classification and mapping of small data for compression.

Gaidhane [26] has suggested a neural network based image compression technique with MLP algorithm for better faster transmission. In this technique some of the information below the threshold value is removed or replace by zero and therefore more information removed from the feature vector matrix and hence from image data which results in poor image quality. A similar concept was suggested in [27] which is called as vector quantization in which a set of code vectors is generated using the self-organizing feature map algorithm. Then, the set of blocks associated with each code vector is modeled by a cubic surface for better perceptual fidelity of the reconstructed images. Allaf [28] also suggested similar method neural network image compression technique. The performance of the suggested method in terms of PSNR, convergence speed and compression ratio are satisfactory.

For achieving better results [29] suggests a novel technique i.e. neural network with bipolar interpolation to balance the tradeoff of speed and quality. In this technique, Compression is achieved by selecting primitive and non-primitive regions to interpolate them. This method found superior to conventional methods in some aspects, such as the clarity and the smoothness in the edge regions as well as the visual quality of the interpolated images. Hui and Yongxue [30] were presented similar neural network concept with haar wavelet and reconstruct the medical image by wavelet packet. It is based on the fact that wavelet packet domain of the same orientation are often similar, and thus coded by similar code words with a vector quantization algorithm. A neural network approach with arithmetic coding using perceptron neural network to compress pixel into single value is explained in [31]. A counter propagation neural network has been used to successfully compress and decompress image data. The network also shows robustness for various classes of images.

Mishra and Zaheeruddin [32] have suggested a new fuzzy neural network for medical image compression. This process is based on approximation problem in which it involves determining or learning the input- output relations using numeric input-output data for image compression application. A similar concept was proposed in [33] in which neural network is designed with modified preprocessing algorithm. The method was divided into two phases. In the first part we present the BS-CROI method of image selection and back propagation image compression in which it is different from traditional ROI. It is found from analysis that, the reconstructed image by this method was promising in terms of PSNR and MSE.

This concept is extended in [34] for better retrieval image. In this work, neural networks are designed to a combination of cascaded networks with one node in the hidden layer. A redistribution of the gray levels in the training phase is implemented in a random fashion to make the minimization of the mean square error applicable to a broad range of images. From the analysis it is found that the performance superiority of cascaded neural networks compared to that of fixed architecture training paradigms especially at high compression ratios. With the existing approaches for compression, the application for image compression based on advanced intelligence approaches using neural network is observed to be an effective approach for compression. The approach for medical image compression using neural network is developed in this work. The effectiveness of neural approach to medical compression is focused.

2. METHODOLOGY

For medical image compression, in this work an ANN based IC architecture is developed. In ANN based compression system the image is coded with respect to its pixel values and pixel coordinate. In [35] an approach for medical image compression based on BPNN is proposed. The approach is developed as improved BPNN and is compared with conventional JPEG based coding system. In such an approach an image is first read into a matrix of dimension m x n and the co similar pixel coefficients are searched forming a pair of pixel value of its counts. This approach is similar to the approach of run length coding for the obtained co-similar pairs, a NN process is carried out, wherein these pairs are given as input to the NN system. The process of NN processing for image compression is briefed as:

2.1 Image Compression Process

Step 1: Input image is converted to matrix format (I) containing $X_{m,n}$, where m is row and n is column.

Step 2: Using (I), pixel values and the number of occurrences of the neighbouring pixel values are counted and represented by pair values (P) as follows.

$$P = (U1,V1) (U2,V2) (U3,V3) \ldots (Ui ,Vj).$$

Where,

U = Pixel values.

V = Number of occurrences of the neighboring pixel values.

Step 3: The pair values (P) obtained from the above step can be represented in sequence order (S).

S = U1, V1, U2, V2, U3, V3 … Ui, Vj.

Step 4: The sequence order (S) can be provided as an input (Xi) to the Multi-Layer Feed-Forward Back propagation Neural Network.

Xi = X1, X2, X3 … Xn.

Step 5: Calculate weight (Wji) using the formula.

$$W_{ji} = \sum_{i=1}^{n} X_i X_i^T \quad \text{Where, } 1 \le j \le k. \quad X_i \text{ is the input Layer.} \tag{1}$$

Step 6: The Hidden Layer of the Multi-Layer Feed-Forward Back propagation Neural Network is created by using the formula (H_j).

$$H_j = \sum_{i=1}^{n} X_{ij}\, X_i \quad \text{Where, } 1 \le j \le k. \quad X_i \text{ is the input Layer.}$$
$$H_i = H_1, H_2, H_3, \ldots H_k \tag{2}$$

The result of the H_j obtained refers the compressed file.

2.2 Image Decompression Process

Step 1: Get (Hj) of the Multi-Layer Feed-Forward Back propagation Neural Network

Hj = H1, H2, H3, … Hk

Step 2: Calculate the weight (Wij) using the formula.

$$W_{ij} = \sum_{j=1}^{k} H_j H_j^T \quad \mathit{Where,}\ 1 \le i \le k \quad H_i\ \mathit{is\ the\ Hidden\ Layer.} \tag{3}$$

Step 3: The Output Layer of the Multi - Layer Feed - Forward Back propagation Neural Network is created by using the formula (Yi).

$$Y_i = \sum_{j=1}^{k} W_{ij} \, H_j \quad \begin{array}{c} Where,\ 1 \le i \le n. \\ H_i \ is\ the\ Hidden\ Layer. \end{array}$$

$$Y_i = Y_1, Y_2, Y_3, \ldots Y_n \tag{4}$$

Step 4: The Output Layer (Yi) is represented in Sequence Order (S).

S = U1, V1, U2, V2, U3, V3 … Ui, Vj.

Step 5: The Sequence Order (S) Value can be represented in Pair Values (P). Each Pair represents the Pixel Value and the number of occurrences of the neighbouring pixel values.

P = (U1,V1) (U2,V2) (U3,V3) … (Ui ,Vj).

Where,
U = Pixel values.
V = Number of occurrences of the neighbouring pixel values.

Step 6: All the Pair Values (P) represented in Pixel Values are converted into Matrix Format (I).

Step 7: Now the matrix format (I) is converted into the image file format.

Due to this conversion the retrieval accuracy is lower. To improve such estimation accuracy the image must be processed in spectral domain rather than processing on direct pixel values. Where-in in this conventional approach image is directly processed, so the finer details of biomedical image samples are more or less astray. The multi resolution information is not observed in previous approach of JPEG2000. So there needs a coding technique which presents a high resolution coding resulting in higher estimation accuracy than the JPEG system. The approach of such spectral coding is adopted for medical image compression into NN based coding. In this approach the medical image are first processed to extract the spectral coefficient over which NN is applied and this novel technique of coding results in higher efficiency when compared with existing approaches.

The proposed approach is as outlined below:

In image compression process, the input image is not processed directly, instead the input image after converted to matrix format and is decomposed to four multi resolution components C_1(horizontal coefficients), C_2(vertical coefficients), C_3 (diagonal coefficients) and C_4(approximate coefficients).

Step 1: Input image is converted to matrix format (I), where I = f(X m,n), where m is row and n is column.

Step 2: Using (I), decompose the image (I), in multi resolution components C_1, C_2, C_3, C_4

Where

C_1 is horizontal coefficients
C_2 is vertical coefficients
C_3 is diagonal coefficients
C_4 is approximate coefficients

Further the steps from 2 to 6 of image compression process and steps from 2 to 7 of decompression process mentioned in the conventional approach are repeated over the coefficient C_i, i=1,2,3,4.

2.3 JPEG2000 Image Compression

The design unit implements the JPEG2000 coding system for image data compression (Fig. 1). The coding system reads the image obtain from the transformation module and pass the data to the decoder unit to retrieve the image back.

Prior to the processing of image data the image is preprocessed to improve the rate of operation for the coding system. Under preprocessing tiling of the original image is carried out. The term “tiling” refers to the partition of the original (source) image into rectangular non-overlapping blocks (tiles), which are compressed independently, as though they were entirely distinct images. All operations, including component mixing, wavelet transform, quantization and entropy coding are performed independently on the image tiles. Tiling reduces memory requirements, and since they are also reconstructed independently, they can be used for decoding specific parts of the image instead of the whole image. All tiles have exactly the same dimensions, except may be those at the boundary of the image. Arbitrary tile sizes are allowed, up to and including the entire image (i.e., the whole image is regarded as one tile). This unit transforms the input image from time domain to frequency domain and decomposes the original image into its fundamental components.

The wavelet transform uses filter banks for the decomposition of preprocessed original image into 3 details and 1 approximate coefficient. The filtering is carried out by convolving the input image with the filter coefficients passed. The Quantization unit finites the image data from non-uniform level to uniform level and in-turn the entropy encoder encode the quantized data using variable length code for data compression. It implements Huffman coding system for data compression.

The decoder unit decodes the encoded (compressed) data back using Huffman decoding. The dequantizer unit retrieves back the quantized data using the quantization table used under quantization. Inverse transformation is the process of retrieving back the image data from the obtained image values. This unit transforms back the data from frequency domain to time domain. The image data transformed and decomposed under encoding side is rearranged from higher level decomposition to lower level with the highest decomposed level been arranged at the top. Finally, the reconstruction of the obtained decomposed component into their proper graphical representation by arranging the obtained tiles back to their place and are then compared with the original image.

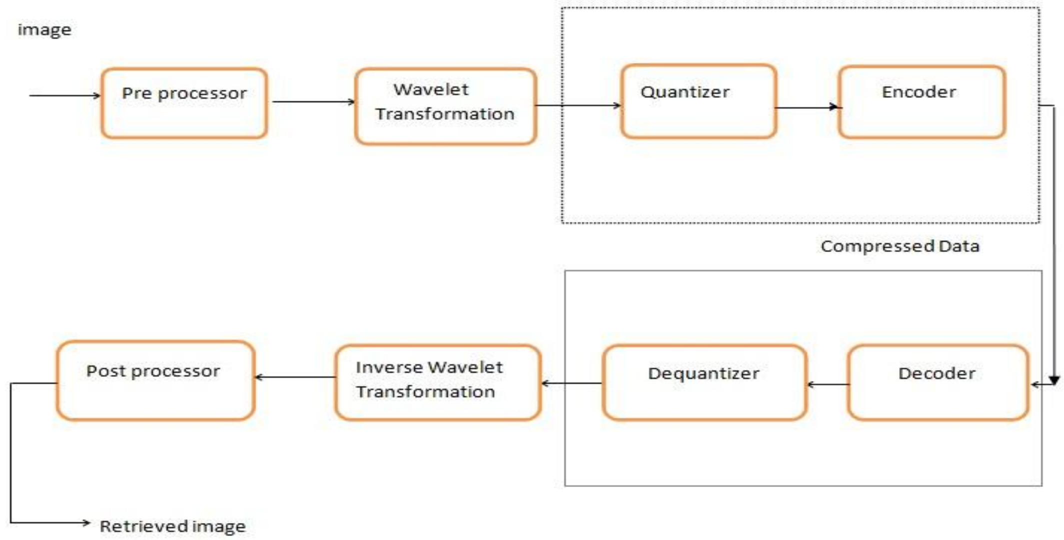

Fig. 1. JPEG2000 image compression model

2.4 Proposed System Architecture

The functional description of the proposed block diagram (Fig. 2) is as follows

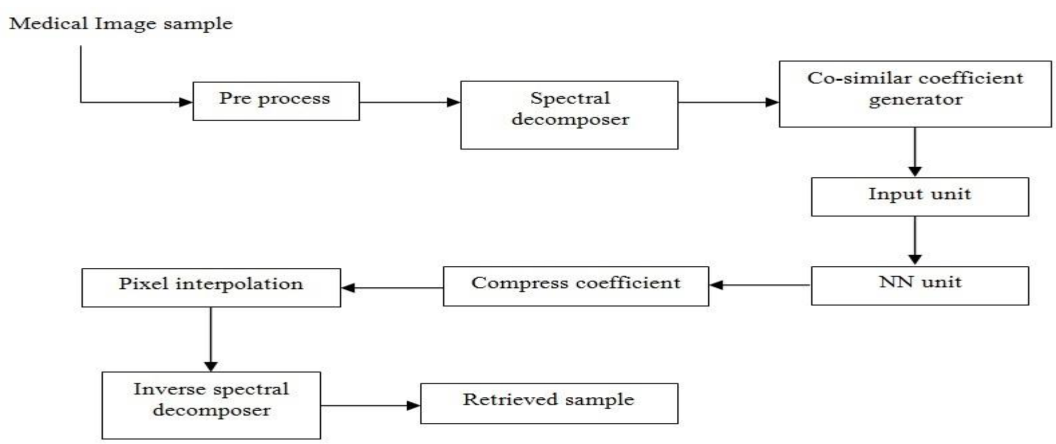

Fig. 2. Proposed block diagram

Pre process unit: This unit reads the medical sample and extracts the gray pixel intensity for processing. The read samples are passed as pixel array as output of this block and passed for decomposition in spectral decompose unit.

Spectral decomposer unit: This unit reads the gray coefficients and performs a pyramidical decomposition to extract the spectral resolutions for given input sample. The decomposition structured is a 2 dimensional recursive filter bank units, performing DWT operation. The recursive operation is carried out by the recursive filtration using pairs of successive high and low pass filter.

Co-similar coefficient generator unit: for the obtained coefficient after spectral decomposition, the coefficients which reflect similar spectral coefficients are segregated, these coefficients are called redundant pixel in the image. The suppression of co-similar coefficient results in first level compression based on redundant information. For the obtained co-similar coefficients a neural network modelling is developed.

Input unit: This unit reads the selected coefficient and normalizes the coefficients to pass to neural network. The unit extracts the coefficient in a column wise manner and is normalized to maximum pixel value.

NN unit: This unit realizes a feed forward neural network using the command 'newff' in matlab tool. The NN unit extract the min-max value of given input and creates a feed forward neural network taking least mean learning algorithm. A tangential sigmoid driving function is used as a kernel function for creating this network. The network is created for converging to the error with a goal of 0.1 and with number of epochs=50. The created network is trained with these coefficient values based on the given input and the created feed forward network.

Compress coefficient: The coded coefficient after the neural network process is stored into a buffer called compressed coefficient. This formulates an array logic wherein the coded output of the NN is stored for future usage.

Pixel interpolation: The compressed data is processed back in this unit. Wherein the simulated result of the created neural network is normalized back to its original scale based on the obtained simulated output of the neural network. The retrieved pixel coefficients are rearranged depending on the sequence order as obtained from the encoding side.

Inverse spectral decomposer: The coefficient obtained from the above units are processed back, where the coefficients are passed back as resolutional information to successive high and low pass filter. The recursive output of each level of filtration is added to the other level filtration result and is recursively filtered to obtain final retrieved level. An inverse DWT approach is followed in this unit.

3. RESULTS AND DISCUSSION

For the evaluation of the suggested approach a simulation model is developed using MATLAB and is been tested on various original gray-scale sample of medical images (Fig. 3) such as human nerve cells, human body organs etc., of different dimensions collected from medical institute with 500 dpi resolution. The training error plot for neural system developed is as shown in (Fig. 4). The Q1 processing sample read with various specifications (Fig. 5A). The output image using conventional JPEG2000 approach is as shown in (Fig. 5B). The output image after applying proposed approach is as shown in (Fig. 5C). The observations are as shown in (Fig. 6).

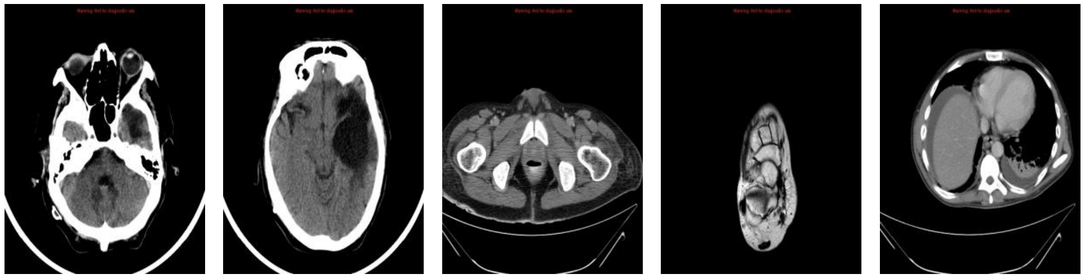

Fig. 3. Original image samples Q1, Q2, Q3, Q4 and Q5

Simulation results

Image Type	:	Medical Image
File Type	:	TIFF
Test sample	:	Q1
Original size	:	87.1kb
Resolution	:	512 X 512
Compressed size	:	40.3 kb
Retrieved size	:	87.1 kb

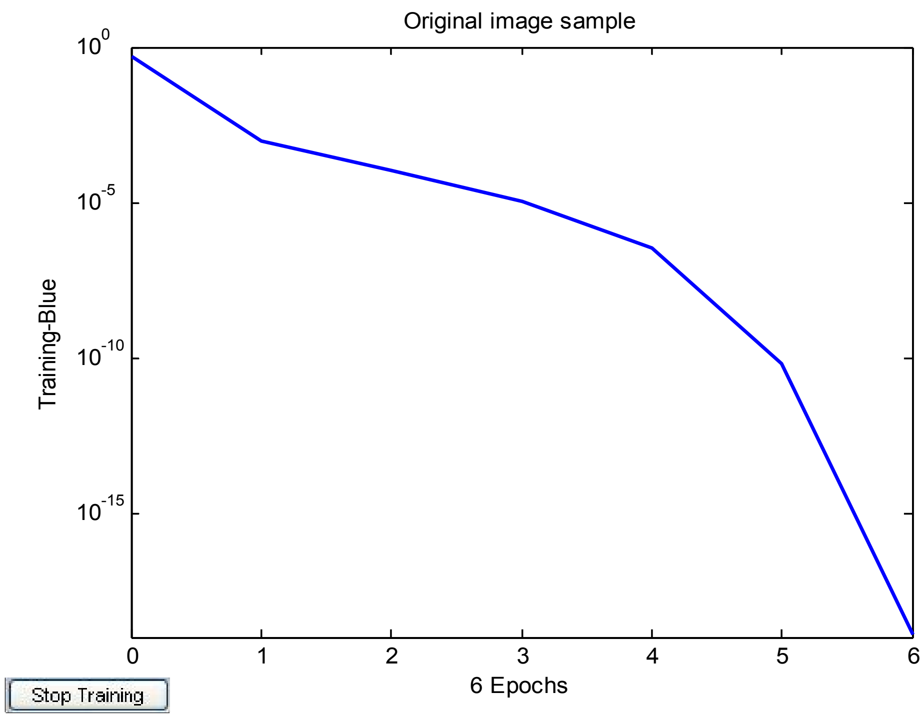

Fig. 4. Training error plot for neural system developed

(A) (B) (C)

Fig. 5. (A) Original processing sample Q1; (B) retrieved image using JPEG2000; (C) retrieved image using proposed spectral-BPNN

A comparison plot between image samples on X-axis and compression ratio on Y-axis for five biomedical images Q1, Q2, Q3, Q4 and Q5 with respect to their observed compression ratios for JPEG2000 and proposed spectral-BPNN approach are illustrated below. It is found that the proposed spectral-BPNN is more efficient than JPEG2000 for achieving high compression ratios for all the biomedical image samples.

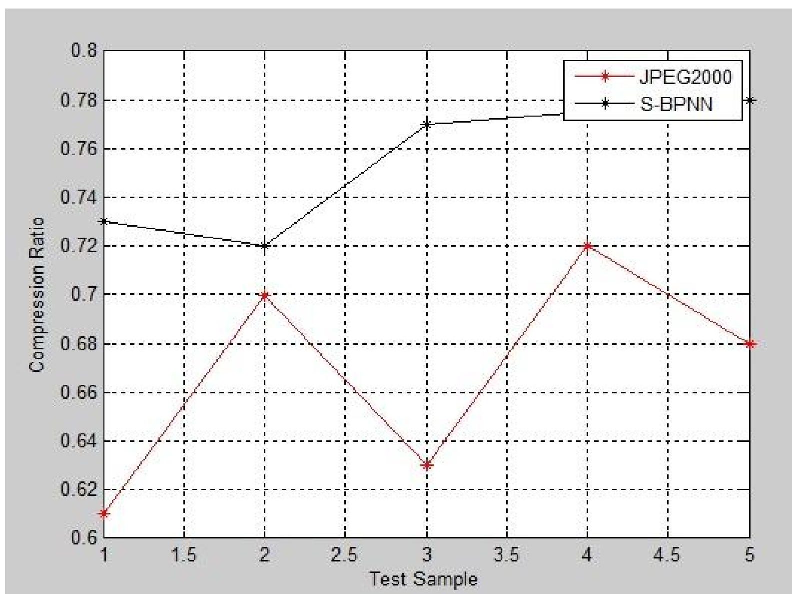

Fig. 6. Comparison of compression ratio when the two methods are applied

4. CONCLUSION

This work implements an enhanced image coding system for biomedical image compression compared to the existing JPEG2000 system. It is observed that proposed algorithm is able to achieve good quality performance with a relatively simple algorithm. Proposed algorithm does not require complicated bit allocation procedures like subband coding does, and it does not require prior knowledge of the image source like JPEG, JPEG2000 does (to optimize quantization tables). Since ANN also has the desirable properties resulting from its successive approximation quantization, different topologies were applied to solve the problem. The results obtained from hybrid neural networks found much better results when compared to conventional JPEG2000 approach.

Since this work mainly focuses on gray-scale images, in the future, it can be extended for other parameters like PSNR, computation time and to color medical images by considering regional information such as texture, boundary information etc., and the observed results can be compared with other standard compression schemes which are used for compression in biomedical imaging.

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COMPETING INTERESTS

Authors have declare that there are no competing interests.

REFERENCES

1. Wallace GK. The JPEG Still Picture Compression Standard. IEEE Transactions on Consumer Electronics. 1992;38(1):17-34
2. Usevitch BE. A Tutorial on Modern Lossy Wavelet Image Compression: Foundations of JPEG 2000. IEEE Signal Processing Magazine. 2001;1053-5888.
3. Jyotheswar J, Mahapatra S. Efficient FPGA implementation of DWT and modified SPIHT for lossless image compression. Journal of Systems Architecture. 2007;53:369–378.
4. Taubmann D. High performance scalable image compression with EBCOT. IEEE Transactions on Image Processing. 2000;9(7).
5. Srikala P, Umar S. Neural Network Based Image Compression with Lifting Scheme and RLC. International Journal of Research in Engineering and Technology. 2012;1(1):13-19.
6. Matsuoka R, Sone M, Fukue K, Cho K, Shimoda H. Quantitative Analysis of Image Quality Of Lossy Compression Images. International Society for Photogrammetry and Remote Sensing. 2013; Accessed 20 September 2013. Avalable:http://www.isprs.org/proceedings/XXXV/congress/comm3/papers/348.pdf.
7. Chang SG, Yovanof GS. A Simple Block-Based Lossless Image Compression Scheme. Thirtieth Asilomar Conference on Signals, Systems and Computer. 1996;1:591-595.
8. Chen YT, Tseng DC, Chang PC. Wavelet-based Medical Image Compression with Adaptive Prediction. Proceedings of International Symposium on Intelligent Signal Processing and Communication Systems. 2005;825-828.
9. Spires W. Lossless Image Compression Via the Lifting Scheme; 2005. Accessed 20 September 2013. http://www.cs.ucf.edu/~wspires/lossless_img_lifting.pdf.
10. Laura L, Camacho MTV, Badran A, Armando DG. “Images Compression for Medical Diagnosis usingNeural Networks; 1990. Accessed 20 September 2013. http://journal.info.unlp.edu.ar/journal/journal2/papers/image.pdf.

11. Yeo WK, Yap DFW, Oh TH, Andito DP, Kok SL, Ho YH, Suaidi MK. Grayscale Medical Image Compression Using Feed forward Neural Networks. International Conference on Computer Applications and Industrial Electronics. 2011;633-638.
12. Durai SA, Saro EA. Image Compression with Back-Propagation Neural Network using Cumulative Distribution Function. International Journal of Engineering and Applied Sciences. 2007;3(4):185-189.
13. Wan TC, Kabuka M. Edge preserving image compression for magnetic resonance Images using DANN-based neural networks. Medical Imaging. 1994;2164.
14. Liang JY, Chen CS, Huang CH, Liu L. Lossless Compression of Medical Images Using Hilbert Space-Filling Curves. Computerized Medical Imaging and Graphics. 2008;32(3):174-182.
15. Khashman A, Dimililer K. Medical Radiographs Compression Using Neural Networks and Haar Wavelet. EUROCON IEEE. 2009;1448-1453.
16. Northan B, Dony RD. Image Compression with a Multiresolution Neural Network. Can. J. Elect. Comput. Eng. 2006;31(1):49-58.
17. Jianxun MI, Huang DS. Image Compression using Principal Component Neural Network. International Conference on Control, Automation, Robotics and Vision. 2008;1:698-701.
18. Kulkarni S, Verma B, Blumenstein M. Image Compression Using a Direct Solution Method Based Neural Network. 10-th Australian Joint Conference on AI. 1997;114-119.
19. Cottrell G, Munro P, Zipser D. Image Compression by Back Propagation: An Example of Extensional Programming. Advances in Cognitive Science. 1989; 209-240.
20. Khashman A, Dimililer K. Neural Networks Arbitration for Optimum DCT Image Compression. Proceeding of the IEEE International Conference on Computer as a Tool. 2007;151-156.
21. Liying M, Khashayar K. Adaptive Constructive Neural Networks Using Hermite Polynomials for Image Compression. Springer-Verlag. 2005;3497:713-722.
22. Karlik B. Medical Image Compression by Using Vector Quantization Neural Network. Neural Network World. International Journal on Neural and Mass - Parallel Computing and Information Systems. 2006;16(4):341-348.
23. Zhou Y, Zhang C, Zhang Z. Improved Variance-Based Fractal Image Compression Using Neural Networks. Springer-Verlag. 2006;3972:575-580.
24. Tripathi P. Image Compression Enhancement using Bipolar Coding with LM Algorithm in Artificial Neural Network. International Journal of Scientific and Research Publications. 2012;2(8).
25. Rajput GG, Singh MK. Modeling of neural image compression using GA and BP: a comparative Approach. International Journal of Advanced Computer Science and Applications. 2011;26-34.
26. Gaidhane V, Singh V, Kumar M. Image Compression using PCA and Improved Technique with MLP Neural Network. International Conference on Advances in Recent Technologies in Communication and Computing. 2010;106-110.
27. Laha A, Pal NR, Chanda B. Design of Vector Quantizer for Image Compression Using Self-Organizing Feature Map and Surface Fitting. IEEE Transactions on Image Processing. 2004;13(10):1291-303.
28. Omaima NA. Improving the Performance of Back propagation Neural Network Algorithm for Image Compression/Decompression System. Journal of Computer Science. 2010;6(11):1347-1354.
29. Lin CT, Fan KW. An HVS-Directed Neural-Network-Based Image Resolution Enhancement Scheme for Image Resizing. IEEE Transactions on Fuzzy Systems. 2007;15(4):605-615.

30. Hui G, Yongxue W. Wavelet packet and neural network basis medical image compression. International Conference on E-Product E-Service and E-Entertainment. 2010;1-3.
31. Rekha, Saini V. A Segmented Wavelet Inspired Neural Network Approach to Compress Images. IOSR Journal of Computer Engineering. 2012;2(6):36-42.
32. Mishra A, Zaheeruddin. Hybrid Fuzzy Neural Network based still Image Compression. International Conference on Computational Intelligence and Communication Networks. 2010;116-121.
33. Vijideva. Neural Network- Wavelet based Dicom Image Compression and Progressive Transmission. International Journal of Engineering Science & Advanced Technology. 2012;2(4):702–710.
34. Obiegbu C. Image Compression Using Cascaded Neural Networks. Master Thesis. 2003. Accessed 20 September 2013. http://scholarworks.uno.edu.
35. Senthilkumaran N, Suguna J. Neural Network Technique for Lossless Image Compression Using X-Ray Images. International Journal of Computer and Electrical Engineering. 2011;3(1).

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