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# NEURAL NETWORK- WAVELET BASED DICOM IMAGE COMPRESSION AND PROGRESSIVE TRANSMISSION

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**Abstract**

*Progressive transmission of medical images through Internet has emerged as a promising protocol for teleradiology and transmission line fault detection systems. The major issue that arises here is the difficulty of transmitting large volume of medical data with relatively low bandwidth. Recent image compression techniques have increased the viability by reducing the bandwidth requirement and allowing cost-effective delivery of medical images for primary diagnosis. This paper highlights a wavelet based coder with Modified Pre-processing Algorithm for Back Propagation Neural Network (MPABPNN) for progressive transmission of DICOM images. Back propagation neural network algorithm helps to increase the performance of the system and to decrease the convergence time for the training of the neural network. In progressive transmission technique, the header of the DICOM image is first transmitted followed by the compressed image data and then at the receiving end, images are reconstructed from low quality to high (or perfect) quality. The proposed scheme has been demonstrated through several experiments including DICOM image **MUSCLE_MRI** and very promising results in compression as well as in reconstructed image in respect of **PSNR** and **MSE** over conventional neural network based techniques. The paper is divided in two main parts. 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.Unlike in ROI here there is no need to generate binary image but it is just a selection of image by sub matrix and selected image will be subjected to first stage compression using modified Back propagation algorithm. In the second part compressed image will be subject to double compression by **ZERO TREE** image decomposition technique with **RLE** we illustrate this using the Deaubechies wavelet transform which is a biorthogonal wavelet transform in the two dimensional case, we present the transform algorithms and we end up with discussing a number of more advanced topics. There are four basic steps in wavelet transform: applying the wavelet transform, threshold detection, classification and encoding the resulting data and finally applying an inverse transform. These theoretical aspects are illustrated through a MATLAB 7.5.*

***Index Terms:*** *Bi-orthogonal wavelets, croi. Neural networks modified RLE.*

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## 1. INTRODUCTION

In this rapidly changing world, image compression is one of the key components to compress the data for specified channel bandwidths or storage requirements maintaining the highest possible quality. The requirement of enormous expenditure on bandwidth and/or storage necessitates the use of various compression schemes. To date, many compression techniques have been developed, such as transform image coding, predicative image coding and vector quantization. Among these, transform image coding is an efficient technique, particularly at low bit rates. For decades, JPEG, a DCT based image compression has been a standard of choice. However, Wavelet transforms have become the most prevalent techniques among those transform image coding techniques, as they are localized in both space and frequency domains. Artificial neural networks are popular in function approximation, due to their ability to approximate complicated nonlinear functions. The multi-layer perceptron (MLP) along with the back propagation (BP) learning algorithm is most frequently used neural network in practical situations. Counter propagation neural network (CPN) typically converges much more quickly than multilayer perceptrons (MLP), hence it is used as an alternative to the MLPs trained by BP. Many researchers have used correlation based techniques for clustering to forward-only counter propagation network (FOCPN).Some recent papers show that the combination of neural network based approach and classical wavelet based approach leads to better compression ratio.JPEG based techniques support progressive lossy to lossless compression. Various wavelet based coding methods have been developed utilizing the spatial similarities among the wavelet coefficients.

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These coders include embedded zero tree wavelet coder (EZW), set partitioning in hierarchical trees (SPIHT), an advancement of EZW, and embedded block coding with optimized truncation (EBCOT), employed in JPEG 2000.

In this paper, we have integrated wavelet transform based image compression to MPABPNN based image compression scheme. This integration leads to better compression ratio, preserving the image quality. Results obtained with proposed scheme are compared with classical wavelet based image compression schemes.

In the first stage DICOM images are compressed using Modified Pre-processing Algorithm for Back Propagation Neural Network (MPABPNN) and in the subsequent stages image is compressed using Deaubachies wavelet transform and RLE encoder which is progressive transmission coder. The DICOM image header is transmitted first followed by the image details in successive stages. The receiver can terminate the transmitting data at any instant once the required information is satisfactory. We evaluate the performance of our scheme in a progressive lossy to lossless scenario. When compared with the existing DICOM supported compression standards (JPEG, JPEG-LS, and JPEG-2000) our method maintains diagnostic feature of the DICOM images at low bit rate, thereby, attaining low bandwidth capabilities for Internet transmission.

**DICOM**

DICOM stands for digital imaging and communications in medicine, which is widely adopted by the medical community for the purpose of storing, transmitting and viewing medical images. The consistency of DICOM standard has leveraged the development of computational applications for processing various medical images, thereby, preserving the clinical value. DICOM images are usually stored in the uncompressed raw data format and hence increases the storage size and the bandwidth requirement for transmission.

## 1.1. BS-CROI

Background Subtracted Context Region of Interest is an image selection technique in which following steps are involved.

- Reading image from database.
- Selecting the ROI
- Generating histogram of ROI by sub matrix method.
- Separation of background and background subtracted image.
- Selection of CROI from background Subtracted image.
- Background Subtracted image data is used to train up network.

## 1.2 Implementation of back Propagation algorithm

The back propagation algorithm consists of the following steps Each Input is then multiplied by a weight that would either inhibit the input or excite the input. The weighted sum of then inputs in then calculated first, it computes the total weighted input Xj, using the formula

$$X_j = \sum_i Y_i W_{ij}$$

Where Yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit. Then the weighed Xj is passed through a sigmoid junction that would scale the output in between 0 and 1 next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function.

$$Y_j = \frac{1}{1 + e^{-x_j}}$$

Once the output is calculated, it is compared with the required output and the total Error E is computed. Once the activities of all output units have been determined, the network computes the error E, which is defined by the expression.

$$E = \frac{1}{2} \sum_j \left(Y_j - d_j\right)^2$$

Where Yj is the activity level of the ith unit in the top layer and dj is the desired output of the ith unit. Now the error is propagated backwards. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity

$$EA_j = \frac{\delta E}{\delta Y_j} = Y_j - d_j$$

Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$$EI_j = \frac{\delta E}{\delta x_j} = \frac{\delta E}{\delta Y_j} \times \frac{\delta Y_j}{\delta x_j} = EA_j Y_j \left(1 - y_j\right)$$

Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\delta E}{\delta W_{ij}} = \frac{\delta E}{\delta x_j} \times \frac{\delta x_j}{\delta W_{ij}} = EI_j Y_i$$

Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multi layer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit. By using steps 2 and 4, we can convert the EA's of one layer of units into EA's for the previous layer. This procedure can be repeated to get the EA's for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EW's on its incoming connections.

$$EA_i = \frac{\delta E}{\delta Y_i} = \sum_j \frac{\delta E}{\delta x_j} \times \frac{\delta x_j}{\delta Y_i} = \sum_j EI_j W_{ij}$$

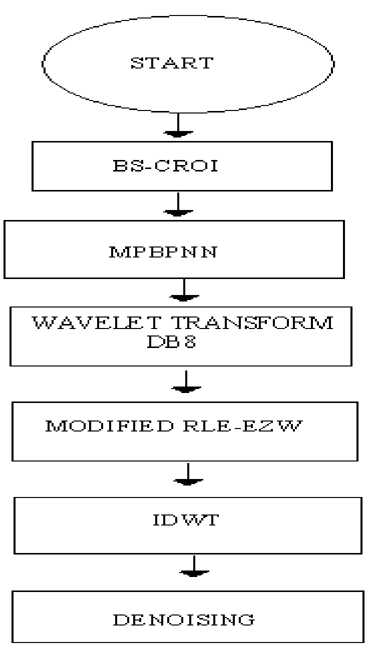


**Fig-1: Hybrid image compression techniques**

## 2. WAVELET TRANSFORM

Wavelet transform (WT) of an image represents image as a sum of wavelets on multi-resolution levels. Multiresolution analysis is implemented via high-pass filters (wavelets) and low-pass filters (scaling functions).In wavelet transforms any one-dimensional function is transformed into a two-dimensional space, where it is approximated by coefficients that depend on time (determined by the translation parameter) and on scale,(determined by the dilation parameter). The zoom phenomena of the WT offer high temporal localization for high frequencies while offering good frequency resolution for low frequencies. Hence, the wavelet transform is well suited to image compression.

## 3. MPABPNN:

Modified Preprocessing Algorithm for Back Propagation Neural Network:
The main steps are as follows

1. Initialize the weights to small random values.

2. Select a training vector pair (input and the corresponding output) from the training set which is a BS-CROI image of size 8*8 to the inputs of the network.
3. Calculate the actual outputs this is the forward phase.
4. According to the difference between actual and desired outputs (error). Adjust the weights WO and Wh to reduce the difference this is the backward phase.
5. Pre and post classification. Repeat from step 2 for all training vectors.
6. Repeat from step 2 until the error is acceptably small Back Propagation learning algorithm. In the forward phase the hidden layer weight matrix h W is multiplied by the input vector X=(X1, X2, X3…….X n) to calculate the α.

## 4. MULTIRESOLUTION ANALYSIS AND MODIFIED WAVELET ALGORITHM

The embedded zero tree wavelet algorithms (EZW) is a simple, yet remarkable effective, image compression algorithm, having the property that the bits in the bit stream are generated in order of importance, yielding a fully embedded code. Using an embedded coding algorithm, an encoder can terminate the encoding at any point thereby allowing a target rate or target distortion metric to be met exactly. Also, given a bit stream, the decoder can cease decoding at any point in the bit stream and still produce exactly the same image that would have been encoded at the bit rate corresponding to the truncated stream. In addition to producing a fully embedded bit stream, EZW consistently

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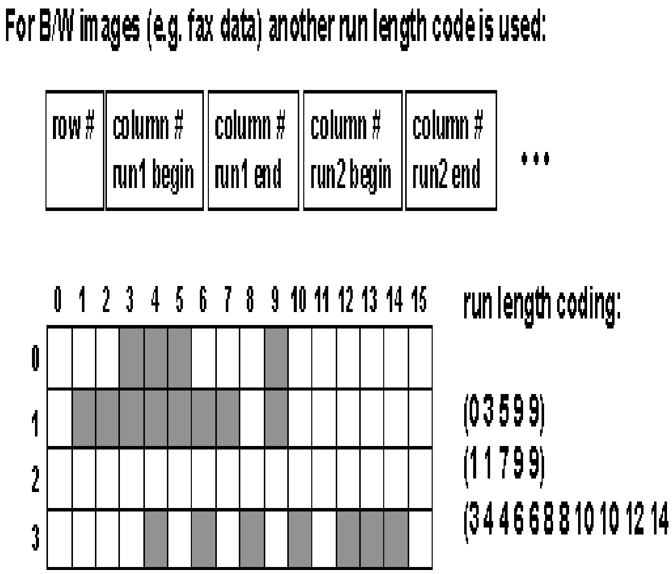
produces compression results that are competitive with virtually all known compression algorithms.

## 5. RUN LENGTH ENCODING (RLE)

Images with repeating greyvalues along rows (or columns) can be compressed by storing "runs" of identical greyvalues in the format:

**greyvalue1 repetition1 greyvalue2 repetition2 • • •**




## 6. RESULTS AND DISCUSSION

The quality of compressed image can be measured by many parameters, which compare to the different compression technique. The most commonly used parameters are Mean Square error (MSE), peak signal to noise ratio error (PSNR), compression ratio(CR) .The PSNR value used to measure the difference between a decoded image and its original image as follows. In general, the larger the PSNR value, the better will be the decoded image quality.

$$\text{RMSE} = \left[\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[\hat{f}(i,j) - f(i,j)\right]^2\right]^{1/2}$$

$$\text{PSNR} = 10\log_{10}\left[\frac{M \times N}{RMSE^2}\right]$$

Where M*N is the size of the image f (i, j) and f (i, j) are the matrix element of the decompressed and the original image at (i, j) pixel. In order to evaluate the performance of image compression system, compression ratio matrix is often employed.

In our results, compression ratio (CR) is computed as the ratio of non zero entries in the original image to the non zero entries in the decompressed image.

**CR =** original image /compressed image size

**CR%=** (1 (1/CR))*100

Image compression using Neural Network is conducted on many images. The graph shown in figure 1 represents the output of the training of the network and 100 epochs have been taken to get trained the network using the training function.

In this case the performance goal of the network has been 0.0042.

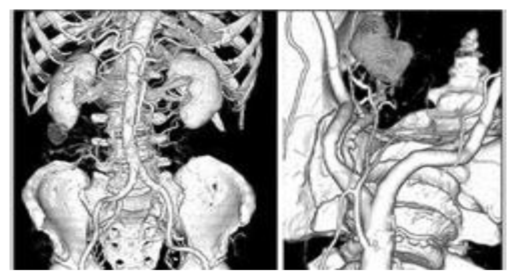


**Fig:2: original image**

**Fig-3: BS-ROI- image**

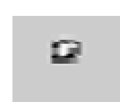


**Fig-4: Resized n*n smallest image to train up the Network**

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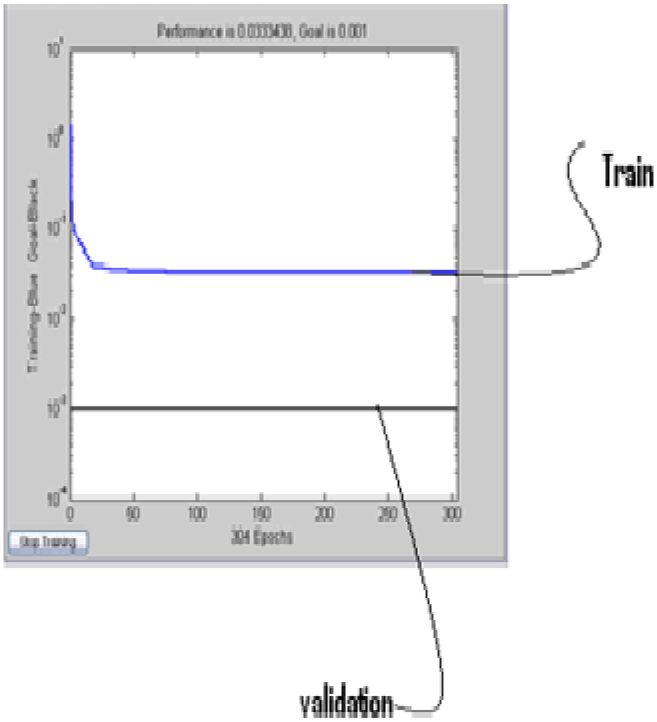


**Fig-5: Output of training dataset using training function**

The graph shown in figure-5: represents the output of the training of the network and 2500 epochs have been taken to get trained the network using the training data. In this case the performance goal of the network has been 0.000718436.

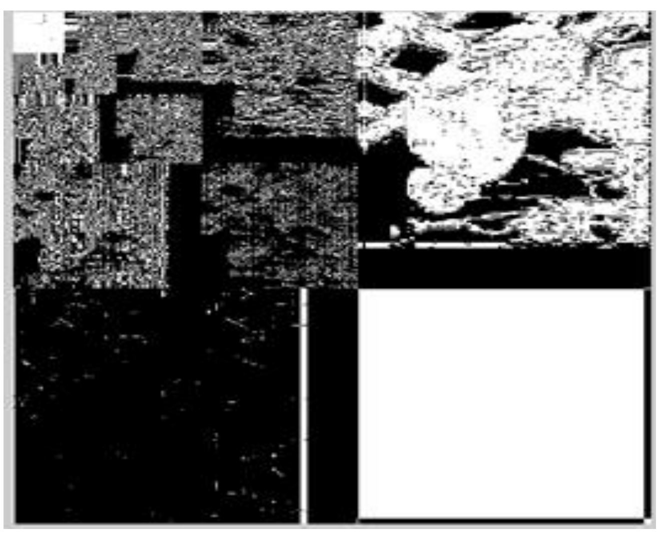

**Fig-6: wavelet decomposed image**

**Fig-7: Finally denoised image**

**Table-1: Parameters image such as of CR, MSE, and PSNR taken at different epochs**

| EPOCH | CR% | MSE | PSNR |
|---|---|---|---|
| 1100 | 80.22 | 0.0175 | 69.59 |
| 1202 | 81.69 | 0.0072 | 69.68 |
| 1300 | 80.19 | 0.0031 | 69.49 |
| 1340 | 82.21 | 0.0129 | 70.07 |
| 1620 | 79.86 | 0.0023 | 70.14 |
| 1800 | 78.18 | 0.0110 | 70.74 |
| 2200 | 78.10 | 0.0086 | 71.79 |

The above values of CR, RMSE, PSNR shows that image is compressed with very low loss of image quality. As the values of epochs is increasing from 1100 epochs to 2200 epochs compression ratio have been decreased from 73.22 to 71.10 and Peak signal to noise ratio has been increased from 69.59 to 71.99 This is because of network is getting more time to adjust their weight and more optimized weight are obtained to train the network.

## 7. CONCLUSION

The implementation of back propagation neural network algorithm on image compression system with good performance has been demonstrated. The back propagation neural network has been trained and tested for the analysis of different images. It has been observed that the convergence time for the training of back propagation neural network is very faster. Different attributes of compression such as compression ratio, peak signal to noise ratio are calculated. It has been observed that there is significance change in compression ratio from 73.22 to 82.21 in case of muscle image. It has also been observed that there is significance improvement in peak signal to noise ratio from 69.59 to 71.79 in case muscle image. The adaptive characteristics of the proposed approach provide modularity in structuring the architecture of the network, which not only speed up the processing but also less susceptible to failure and easy for rectification. Instead of generating multiple training patterns and imparting off-line training, here due to the considerable reduction of image size The technique of initialization of weights exhibits fast rate of convergence and using the trained weight sets, good quality of regenerated images are available at the receiving end.

## 8. FUTURE WORK

In this paper, we proposed a Wavelet-MPBPNN based technique for color image compression. The algorithm is tested on varieties of benchmark images. Simulation results for one of the standard image, i.e. muscle with different distance functions are presented. These results are compared with classical wavelet transform based image compression scheme. Several performances measures are used to test the reconstructed image quality. The above algorithms can be used to compress the image that is used in the web applications. Furthermore in future we can analyze different Image coding algorithms for improvement of different parameters.

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## BIOGRAPHY

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