BEST IMAGE COMPRESSION OF RADIOGRAPHS USING WAVELET AND NEURAL NETWORKS

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Abstract— **Bandwidth conservation is an important issue in case of multimedia communication. Uncompressed multimedia (graphical, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speeds and digital communication system performance, it demands for data storage capacity and data-transmission bandwidth continuously to outstrip the capabilities of available technologies. So to solve this problem an efficient multimedia communication scheme is proposed which is based on Wavelet. Image compression is the technique of reducing the size of image file without degrading the quality of the image. There are many techniques available in the lossy image compression in which Wavelet transform based image compression is the best technique. Various types of Wavelets are used for image compression. This paper shows Better image compression by using different wavelet with the help of Neural network. The paper defines the progress made towards calculating different parameter for Wavelet and after that determines the wavelet which gives minimum value of mean square error and maximum value of peak signal to noise ratio. By this best compression Wavelet is obtained. For Analysis considered MSE value should be a minimum and peak signal to noise ratio value should be a maximum. By implementing neural network, the optimum image compression system use a supervised neural network based on the back propagation learning algorithm, due to its implementation, simplicity and the availability of sufficient target database for training the supervised learner is obtained.**

The paper present the idea of image compression based on hierarchical back propagation neural network and results are analyzed. The further analysis is conducted in the network model and tested training algorithm. Finally image compression and image reconstruction are accomplished respectively, a minimum accuracy of 89% was considered as accepted. The neural network yielded 98.65% correct recognition rate of optimum compression ratios,

This concludes that a high compression ratio is achieved with Bi-orthogonal Wavelet functions. The results are obtained with a Bi-orthogonal 6.8 Reconstruction Wavelet function and proved the best. Then Neural Network is implemented to prove the best result and hence achieved. Experimental results suggest that the proposed system can be efficiently used to compress while maintaining high image compression.

Index Terms— X-Ray; Image Compression; Wavelet Transform; Back Propagation.

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I. INTRODUCTION

Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. The recent growth of data intensive multimedia-based web applications have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signals central to storage and communication technology.

II. Wavelets and wavelet choice

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals.

Basically wavelets may be classified in to two basic classes:

(a) Orthogonal
(b) Bi-orthogonal.

The coefficients of orthogonal filters are real numbers. The filters are of the same length and are not symmetric.

The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Sampled input image is decomposed into various frequency sub-bands or sub-band signals. Splitting of signal into two parts shown in Figure 2.1. A two dimensional decomposition can be applied over the image. A simple example of level 2 decomposing is shown in Figure 2.2. [4]

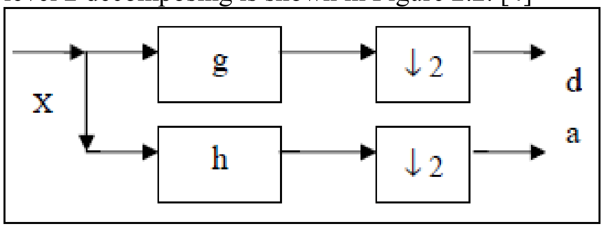

Figure 2.1: Splitting of signal into two parts.

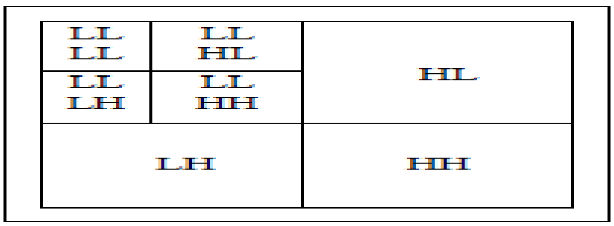

Figure 2.2: Two levels of 2-D DWT decomposition.

III. Picture Quality Measures

Picture quality is measure by calculating different parameter[3].Also calculating compression ratio for each image. It should be near about same for all the image.[6]

Mean Square Error (MSE) = $\frac{1}{N}\sum_{j=1}^{M}\sum_{K=1}^{N}\left(x_{j,k}-x'_{j,k}\right)^2$

Peak Signal to Noise Ratio (PSNR) = $10\log\frac{(2^n-1)^2}{MSE}$

= $10\log\frac{255^2}{MSE}$

Normalized Cross-Correlation (NK) =

$\sum_{j=1}^{M}\sum_{k=1}^{N} x_{jk}\cdot x'_{jk} / \sum_{j=1}^{M}\sum_{k=1}^{N} x_{jk}^2$

Average Difference (AD) = $\sum_{j=1}^{M}\sum_{k=1}^{N}(x_{jk}-x'_{jk})/MN$

Structural Content (SC) = $\sum_{j=1}^{M}\sum_{k=1}^{N}x_{jk}^2/\sum_{j=1}^{M}\sum_{k=1}^{N}x'^2_{jk}$\

Maximum Difference (MD) = $Max\left(\left|x_{j,k}-x'_{j,k}\right|\right)$

Picture Quality Scale (PQS) = $b_0+\sum_{i=1}^{3}b_iZ_i$

IV. Neural Network

The term neural network was traditionally used to refer to a network or circuit of biological neurons. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes.[1]

Backpropagation

It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set.

The goal of any supervised learning algorithm is to find a function that best maps a set of inputs to its correct output. The goal and motivation for developing the backpropagation algorithm is to find a way to train multi-layered neural networks such that it can learn the appropriate internal representations to allow it to learn any arbitrary mapping of input to output.

Initially, before training, the weights will be set to random. Then the neuron learns from training examples, which in this case consists of a set of tuples (x_1, x_2, t) where $x_1$and $x_2$are the inputs to the network and $t$is the correct output (the output the network should eventually produce given the identical inputs). A common method for measuring the discrepancy between the expected output t and the actual output $y$is using the squared error measure:

$$E=(t-y)^2,$$

where E is the discrepancy or error.

As an example, consider the network on a single training case: (1, 1, 0), thus the input $x_1$and $x_2$are 1 and 1 respectively and the correct output, $t$is 0. Now if the actual output $y$is plotted on the x-axis against the error Eon the y-axis, the result is a parabola.

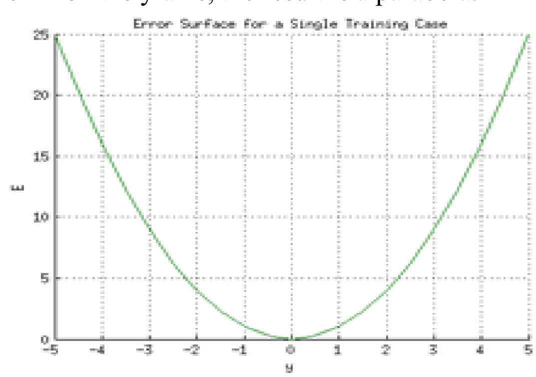

Figure 4(a) Error surface of a linear neuron for a single training case.

However, the output of a neuron depends on the weighted sum of all its inputs:

$$y=x_1w_1+x_2w_2,$$

where w_1 and w_2 are the weights on the connection from the input units to the output unit. Therefore, the error also depends on the incoming weights to the neuron

V. Methodology

5.1 Methodology Used

1) Selection of best wavelet for medical Radiographs.
   - Compress input image with each wavelet with fixed CR.
   - Find the following parameters to make comparison
2) MSE, PSNR, Correlation, Average difference, Normalized absolute error, Structural content.
3) Make database using selected wavelet.
4) Save each with its optimum compression ratio using subjective and objective evaluation.
5) Train and testing of neural network.
6) Apply input image to neural network with unknown CR.
7) Compress this image with CR defined by neural network.
8) Comparison with implemented paper based upon following parameters
   - CR
   - PSNR
   - MSE

VI. Experimental Results

Firstly we have done selection of best wavelet for medical Radiographs. [2]

Choice of wavelet

Table 6.1: Analysis of Radiograph image compression using various wavelets

Wavelet	THR	CR	MSE	PSNR	MD	SC	NAE	CC
db2	0.7	50.4	0.0469	141.4959	1.0959	1	0.0019	1
db3	0.6	49.205	0.0339	144.7469	0.9525	1	0.0017	1
db4	0.6	50.46	0.034	144.5272	0.9071	1	0.0017	1
db5	0.6	50.62	0.0345	144.5651	0.9014	1	0.0017	1
db6	0.6	50.78	0.0351	144.3925	0.9168	1	0.0017	1
db7	0.6	50.81	0.0349	144.4441	1.0017	1	0.0017	1
db8	0.6	50.87	0.0357	144.2412	0.9414	1	0.0018	1
bior1.1	2.6	50.1245	0.5303	117.2472	3.75	1	0.0064	1
bior1.3	2.6	51.995	0.5066	117.7048	3.7109	1	0.0064	1
bior1.5	2.4	51.6671	0.4339	119.2527	3.2912	1	0.006	1
bior2.2	0.8	49.38	0.0794	136.2351	1.6523	1	0.0025	1
bior2.4	0.8	50.7235	0.0791	136.2747	1.55	1	0.0026	1
bior2.6	0.8	51.313	0.0792	136.2574	1.4348	1	0.0026	1
bior2.8	0.7	49.4246	0.0636	138.4601	1.1896	1	0.0023	1
bior3.1	0.5	51.8102	0.064	138.374	1.1602	1	0.0024	1
bior3.3	0.4	48.2939	0.0332	144.9532	0.7946	1	0.0017	1
bior3.5	0.4	48.6704	0.0313	145.5413	0.7535	1	0.0016	1
bi0r3.7	0.4	48.9488	0.0307	145.7351	0.7542	1	0.0016	1
bior4.4	0.6	51.87	0.0372	143.809	0.9595	1	0.0017	1

bior6.8	*0.5*	*49.163*	*0.0254*	*147.6272*	*0.7523*	*1*	*0.0015*	*1*
rbio1.3	0.6	48.5924	0.0336	144.8497	0.8555	1	0.0016	1
rbio2.2	1	49.61	0.0719	137.2215	1.3125	1	0.0024	1
rbio2.4	0.9	47.54	0.0577	139.425	1.082	1	0.0021	1
rbio2.6	0.8	49.91	0.0477	141.3389	0.9793	1	0.002	1
rbio2.8	0.8	51.54	0.0487	141.1204	0.9848	1	0.002	1
rbio3.3	1	42.36	0.0682	137.736	1.2757	1	0.0023	1
rbio3.5	1	49.194	0.068	137.7805	1.4611	1	0.0024	1
rbio3.7	1	50.85	0.0684	137.7259	1.2606	1	0.0024	1
rbio4.4	0.7	50.9181	0.0446	141.9998	1.0022	1	0.0019	1

It is clearly seen that, for bi-orthogonal 6.8 wavelet, we are getting least MSE and highest PSNR of 147.6272 db with fixed CR. From the above observation table it is more cleared with mathematical formulae support, that bi-orthogonal type 6.8 wavelet is best suitable for medical image.

Original image **Using bior 6.8**

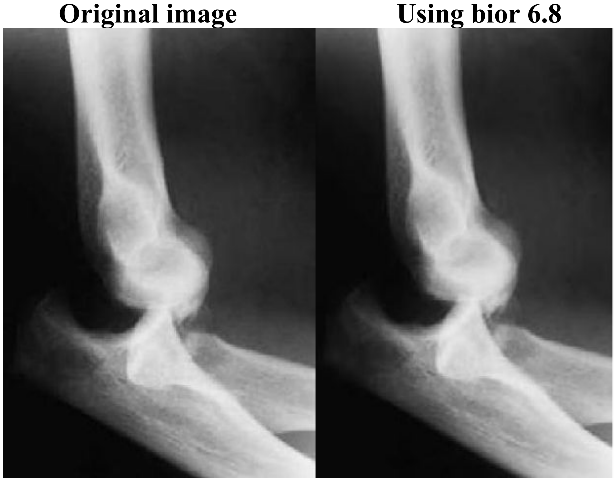

Figure 6.1(a): Show the comparison between radiograph image using bior 6.8 wavelets.

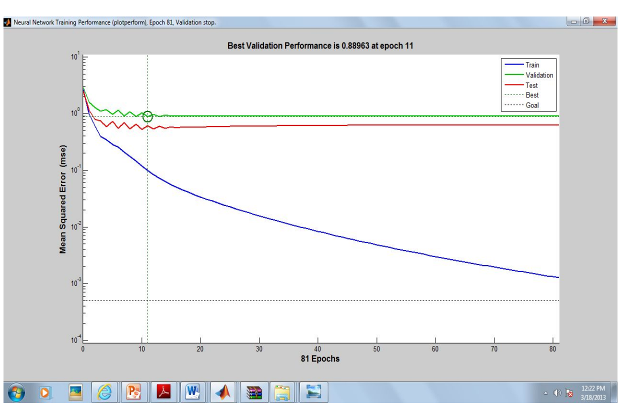

Figure 6.2 (b) Performance Graph

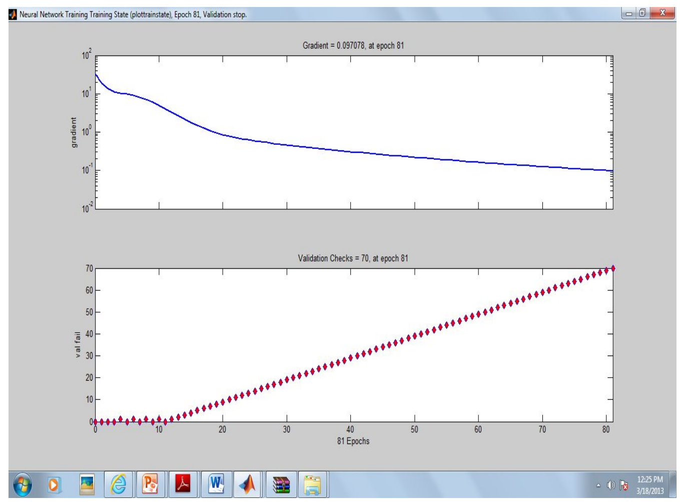

Figure 6.2 (c) Training State

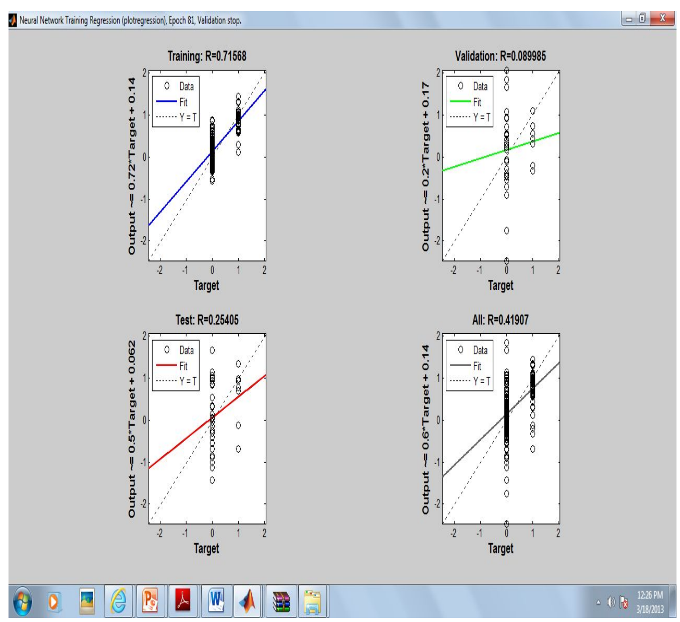

Figure 6.2 (d) Regression Graphs

Conclusion

When we have done selection of best wavelet for medical Radiographs. Then to compress input image with each wavelet with fixed CR. After that to find the following parameters to make comparison MSE, PSNR, Correlation, Average difference, normalized absolute error, Structural content. Then we have database using selected wavelet. And then to save each with its optimum compression ratio using subjective and objective evaluation. To train and testing of neural network. And then apply input image to neural network with unknown CR. To compress this image with CR defined by neural network. It is clearly seen that, for bi-orthogonal 6.8 wavelet, we are getting least MSE and highest PSNR of 147.6272 dB with fixed CR. From the above observation table it is more cleared with mathematical formulae support, that bi-orthogonal type 6.8 wavelet is best suitable for medical image.

Future Scope

In future we can apply JPEG (Joint Photographic Expert Group) compression method instead of threshold for finding better compression. Another scope is to optimized the compression method by using AI (Artificial Intelligence) algorithm

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