Hybrid Image Compression using DWT and Neural Networks

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Abstract

Image compression is playing a key role in the development of various multimedia computer services and telecommunication applications. As image needs a huge amount of data to store it, there is pressing need to limit image data volume for transport along communication links. An ideal image compression system must yield good quality compressed images with good compression ratio, while maintaining minimal time cost. The goal of image compression techniques is to remove redundancy present in data in a way that enables image compression technique. There are numerous lossy and lossless image compression techniques. For the still digital image or video, a lossy compression is preferred. Wavelet-based image compression provides substantial improvements in picture quality at higher compression ratios. Contrary to traditional techniques for image compression, neural networks can also be used for data or image compression. In this paper both of these methods for compression of images to obtain better quality.

Keywords: *Compression Ratio, Image Quality, Neural Networks, Wavelet Transform*

1. Introduction

Compression methods are being rapidly developed to compress large data files such as images, where data compression in multimedia applications has lately become more vital .With the increasing growth of technology and the entrance into the digital age, a vast amount of image data must be handled to be stored in a proper way using efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size.

Image compression using Wavelet Transforms is a powerful method that is preferred by scientists to get the compressed images at higher compression ratios. It is a popular transform used for some of the image compression standards in lossy compression methods. Unlike the discrete cosine transform, the wavelet transform is not Fourier-based and therefore wavelets do a better job of handling discontinuities in data. With Wavelet Transform based compression, the quality of compressed images is usually high, and the choice of an ideal compression ratio is difficult to make as it varies depending on the content of the image. Therefore, it is of great advantage to have a system that can determine an optimum compression ratio upon presenting it with an image. Image compression using wavelet transform and a neural network was suggested recently [1]. Moreover, different image compression techniques were combined with neural network classifier for various applications [1]. Neural network can be trained to establish the non-linear relationship between the image intensity and its compression ratios in search for an optimum ratio. The Wavelet Transform and more particularly Discrete Wavelet Transform (DWT) is a

relatively recent and computationally efficient technique for analyzing and extracting information from image signals [2]. Discrete wavelet transform (DWT) has a good representation at frequency and time scaling with which DWT was recently used by some international organizations as image compression standard such as JPEG2000. MPEG4.

2. Problem Definition

One of the major difficulties encountered in image processing is the huge amount of data used to store an image. Thus, there is pressing need to limit the resulting data volume. Image compression techniques aim to remove the redundancy present in data in a way that makes image reconstruction possible. It is necessary to find the statistical properties of the image to design an appropriate compression transformation of the image; the more correlated the image data are, the more data items can be removed.

Numerous lossy image compression techniques have been developed in the past years. The transform-based coding techniques, and in particular the block transform coding, have proved to be the most effective in obtaining large compression ratios while retaining good visual quality. In particular, cosine-transform-based techniques (JEPG) have been found to obtain excellent results in many digital image compression applications. Recently, neural networks have proved to be useful in image compression because of their parallel architecture and flexibility.

A wavelet transform combines both low pass and high pass filtering in Spectral decomposition of signals. One-Stage Filtering: Approximations and Details For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. Consider the human voice. If you remove the high-frequency components, the voice sounds different, but you can still tell what's being said. However, if you remove enough of the low-frequency components, you hear gibberish.

3. Introduction to dwt and Neural Network

In wavelet analysis, we often speak of *approximations* and *details*. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

The original signal, S, passes through two complementary filters and emerges as two signals. Unfortunately, if we actually perform this operation on a real digital signal, we wind up with twice as much data as we started with. By using down sampling, we can reduce the number of samples. The filtering part of the reconstruction process also bears some discussion, because it is the choice of filters that is crucial in achieving perfect reconstruction of the original signal. The down sampling of the signal components performed during the decomposition phase introduces a distortion called aliasing. It turns out that by carefully choosing filters for the decomposition and reconstruction phases that are closely related (but not identical), we can "cancel out" the effects of aliasing.

The low- and high-pass decomposition filters (L and H), together with their associated reconstruction filters (L' and H'), form a system of what is called *quadrature* ***mirror filters.***

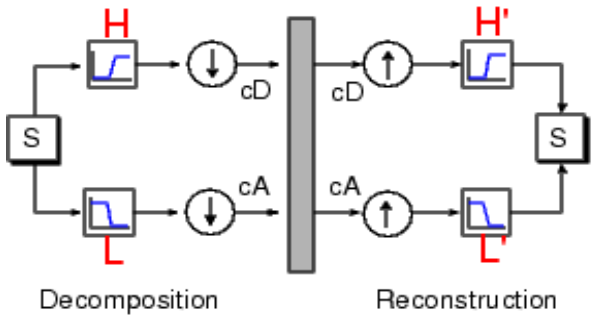
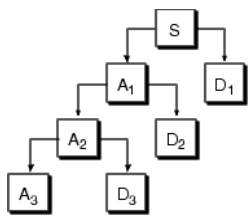


Figure 1. Single level decomposition and reconstruction

3.1. Multiple-Level Decomposition

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree. In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. For n-level decomposition, there are n+1 possible ways to decompose or encode the signal. A three level decomposition of image is shown here.



$$S = A_1 + D_1$$
$$= A_2 + D_2 + D_1$$
$$= A_3 + D_3 + D_2 + D_1$$

Figure 2. Three-level decomposition

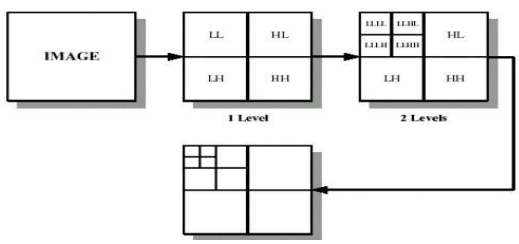


Figure 3. Three level image decomposition

In wavelet packet analysis, the details as well as the approximations can be split. The wavelet decomposition tree is a part of this complete binary tree.

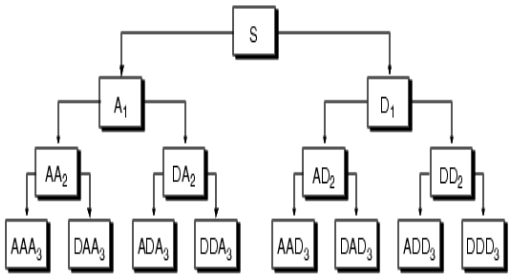


Figure 4. Wavelet Packet analysis

Artificial Neural Networks (ANN) has been used for solving many problems, especially in cases where the results are very difficult to achieve by traditional analytical methods. There have already been a number of papers published applying ANN to image compression. It is important to emphasize, although there is no sign that neural networks can take over the existing techniques, research on neural networks for image compression are still making some advances.

Possibly in the future this could have a great impact to the development of new technologies and algorithms in this area. The main goal of this project is to investigate which neural network structure accomplished with different learning algorithms give the best results compared with standard transform coding techniques. The various feed forward neural networks with back propagation algorithms were directly apply to image compression coding.

A simple model would be a two layer back propagation network with n input and n output neurons. The hidden layer contains m neurons where m is smaller than n. To compress the image, the input is divided into small blocks, each containing n pixels. The network is then trained to produce outputs identical to the input vectors. This is done by randomly sampling the data and feeding them into the network. Once the network is trained, the activation values of the internal neurons are enough to create the output. With a piece of input given, the activation values of the hidden layer are computed. These values are stored as the compressed image data which can be uncompressed in the same network structure. The hidden activations are clammed into the hidden layer of the network and the output is computed.

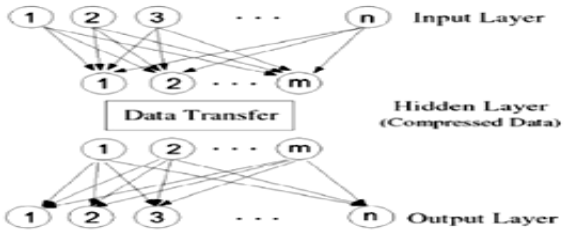


Figure 5. Simple compressor model

This method introduces a co-evolutionary method to compress images with MLP networks. Here there is a class of experts each of which works best with a subset of the problem space. The image is divided into tiles and a number of compressing networks are trained to compress different tiles. As the process continues, each compressor gets trained to fit best with a set of tiles with certain characteristics. The detail of this process is as follows: First, a class of semi-

trained networks with different number of hidden neurons is gathered. Here weights of the connections are set to values which are reasonably close to the optimal values. This helps the process run faster as it needs much less time to converge to the optimum values. In each step a sample is chosen randomly from the input image and is fed into all the networks. The PSNR (Peak Signal to Noise Ratio) is then calculated for each network:

$$PSNR = 10 * \log_{10}\left(\frac{\max^2}{\frac{1}{n}\sum_i (o_i - i_i)^2}\right)$$

where max is the range of the activation values and n is the number of input neurons. The values o_i and i_i are the ith output and the ith input respectively. For each network the goodness is defined as

$$g_{N_i} = a * PSNR_{N_i} - b * \log(hn_{N_i})$$

Where a and b are positive values and hn is the number of hidden neurons in the network. Values a and b indicate the compression rate of the network. Good compressing networks are those with small size (small number of activation values to be stores as the compressed data) and with smaller noise in the output. As PSNR is a logarithmic measure of error, it is better for the size factor to be logarithmic as well. For instance, for JPEG compression, doubling the bit rate would only change the PSNR value by 2 or 3. This shows a logarithmic dependency between the two values. Here, parameters a and b can be tuned to change the compression rate of the set of network. However, this will not give a tight compression rate and rather gives an approximation. Once the goodness values are calculated, a network is selected randomly, using a random function weighted by the goodness values. The selected network is then trained with the input sample to match it better.

4. Design and implementation

Basic architecture for image compression using neural network is shown in the above figure. Most of the image compression techniques use either neural networks for compression or DWT (Discrete wavelet Transform) based transformation for compression.

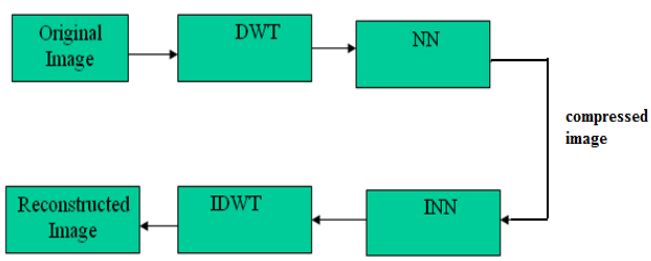


Figure 6. Block Diagram Representation

The following are the phases of implementation.

PHASE 1: Here the original image undergoes discrete wavelet transformation. The DWT is a transform which can map a block of data in the spatial domain into the frequency domain. The DWT returns information about the localized frequencies in the data set.

PHASE 2: Here we get a compressed image using the neural networks.

PHASE 3: The results are saved and the quantization step from the compression is reserved. The parts of the image are then prepared for the inverse discrete wavelet transform. The wavelets packets are subjected to the inverse DWT. Afterwards, the final reconstructed image may be displayed.

For images, there exist an algorithm similar to the one-dimensional case for two-dimensional wavelets and scaling functions obtained from one- dimensional ones by tensorial product. This kind of two-dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation at level $j + 1$, and the details in three orientations (horizontal, vertical, and diagonal).

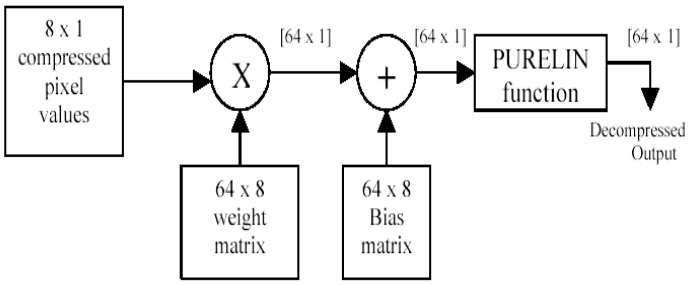


Figure 7. Compression Stage

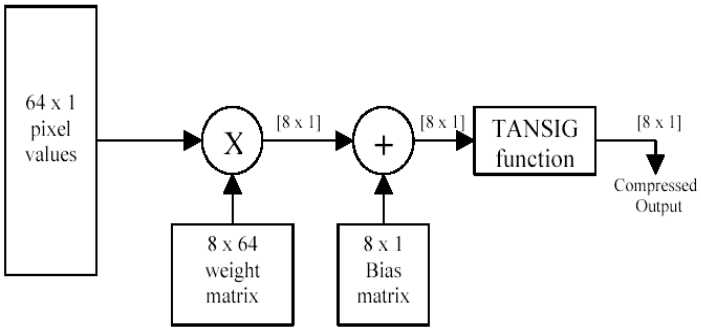


Figure 8. Decompression Stage

From the above two figures it is evident, how compression and decompression takes place. The mean square error can be found by comparing the input and output values.

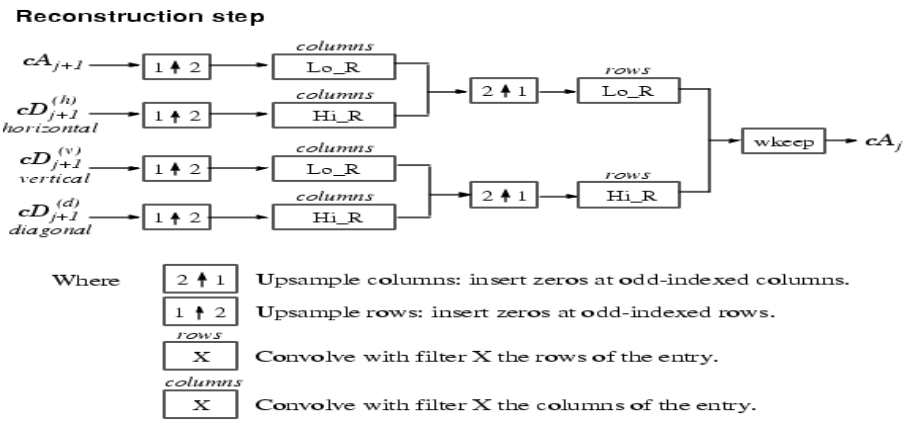


Figure 9. Two dimensional IDWT

5. Simulation results

The simulation results using single level and two level decomposition using DWT and Neural network is shown in the following figures. The original image is given to the network the decomposition output is shown in Figure 11 and after reconstruction the output is shown in Figure 14.

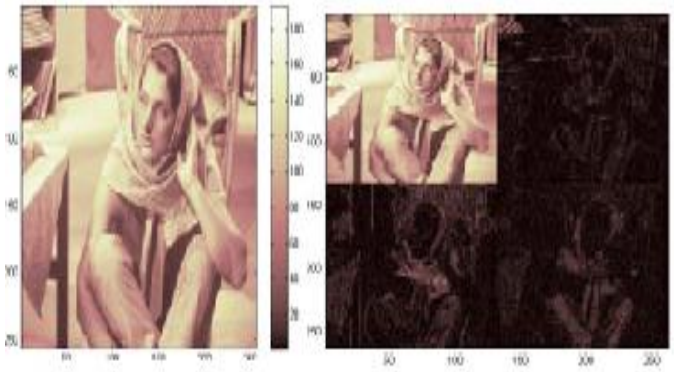


Figure 10 (a). Original Image (b) One level decomposition

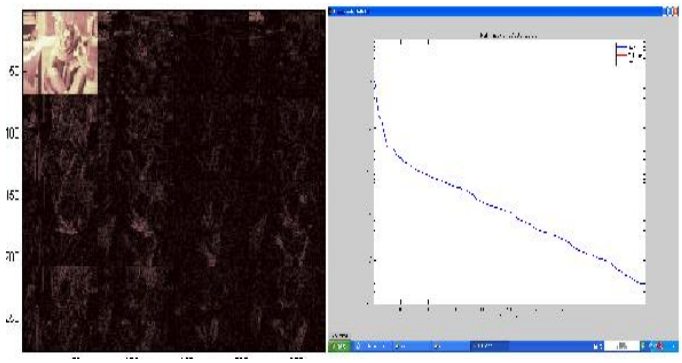


Figure 11 (a). Two level decomposition (b) Training waveform

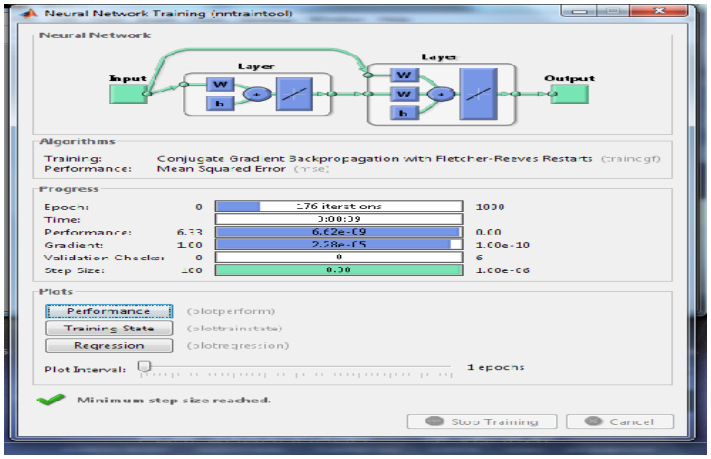


Figure 12. Neural Network

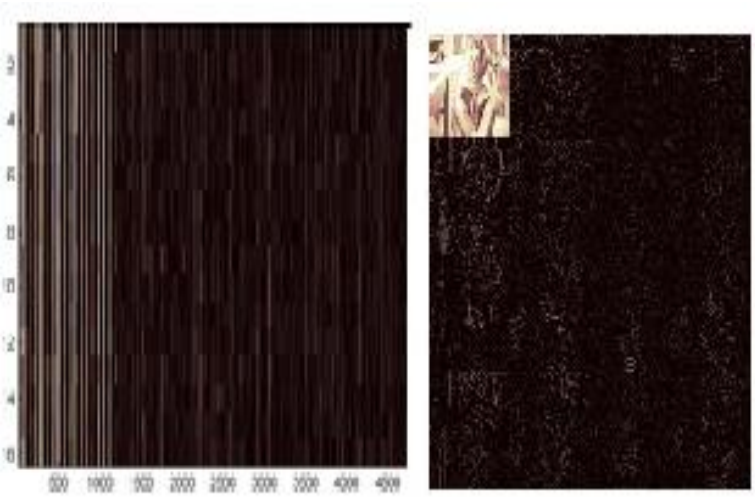


Figure 13 (a). Neural Network output (b) Reconstruction from NN

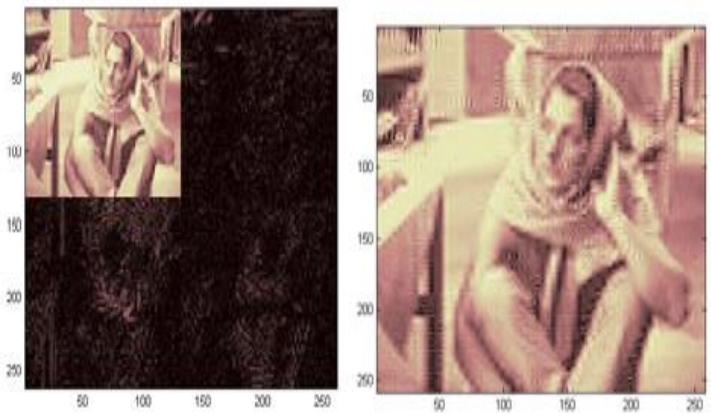


Figure 14 (a). One level reconstruction (b) R Final reconstructed image

6. Conclusion

All the disadvantages of Joint Photographic Expert Group (JPEG) have overcome in Neural Network based Hybrid image compression, (Hybrid technique concept proving Combining wavelets and neural network).

The implementation of the proposed method used biorthogonal image compression where the quality of the compressed images degrades at higher compression ratios due to the nature of the lossy wavelet compression. Noise on compressed data samples does not influence retrieval of original image using Neural Network (NN) techniques where as in Joint Photographic Expert Group (JPEG) technique noise effects decompression.

The Hybrid image compression is to combine Discrete Wavelet Transform (DWT) and Neural Network (NN) with Biorthogonal high compression ratio with good quality compressed image and optimize-area and power is observed.

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