



Perfect Compression Technique in Combination with Training Algorithm and Wavelets

Prachi Jain, Aishwarya Vishwakarma

*Department of computer technology & application, bmeprachijain@gmail.com
Technocrats Institute of Technology, Bhopal, 9406536536, bmeprachijain@gmail.com*

Abstract

Wavelets are mathematical tools for hierarchically decomposing functions. Wavelet Transform has been proved to be a very useful tool for image processing in recent years. It allows a function which may be described in terms of a coarse overall shape, plus details that range from broad to narrow. Advances in wavelet transforms and quantization methods have produced algorithms capable of surpassing the existing image compression standards like the Joint Photographic Experts Group (JPEG) algorithm. For best performance in image compression, wavelet transforms require filters that combine a number of desirable properties, such as orthogonality and symmetry. The Neural Networks are good alternative for solving many complex problems. In this paper image compression is employed through multilayer network. A novel algorithm for neural network with different techniques is proposed in this paper. Experimental results show that this algorithm outperforms than other coders such as SPIHT, EZW, STW exists in the literature in terms of simplicity and coding efficiency by successive partition the wavelet coefficients in the space frequency domain and send them using adaptive decimal to binary conversion. This method holds parameters like PSNR, MSE, BPP, CR, image size. SPHIT for important features.

Keywords: PSNR, MSE, STW, SPIHT, EZW, Neural Network.

1. INTRODUCTION

The computers have become more and more transform is often used for signal and image powerful, the temptation to use digital images has become smoothing keeping in view of its “energy compaction” irresistible. Image compression plays a vital role in properties, i.e. large values tend to become larger and several important and diverse applications, including small values smaller, when the wavelet transform is televideo conferencing, remote sensing, and medical imaging applied.[1, 2] and magnetic resonance imaging [3] and many Since the Transform is memory efficient, exactly more [4]. These requirements are not fulfilled with old reversible without the edge effects, it is fast and simple. Techniques of compression like Fourier Transform, As such the Haar Transform technique is widely used Hadamard and Cosine Transform etc. due to large mean these days in wavelet analysis. Fast Haar Transform is Square error occurring between original and reconstructed one of the algorithms which can reduce the tedious images. The wavelet transform approach serves the work of calculations. One of the earliest versions of

purpose very efficiently. The wavelet transform, FHT is included in HT [9]. FHT involves addition, developed for signal and image processing, and has been subtraction and division by 2. Its application is extended for use on relational data sets [5, 6]. Atmospheric turbulence analysis, image analysis, signal the basic idea behind the image compression is that and image compression has been discussed in most of the images we find that their neighbouring.

Digital Image Processing is defined as analysing and manipulating images. Image Compression has become the most recent emerging trend throughout the world. Some of the common advantages image compressions over the internet are reduction in time of webpage uploading and downloading and lesser storage space in terms of bandwidth. Compressed images also make it possible to view more images in a shorter period of time [7]. Image compression is essential where images need to be stored, transmitted or viewed quickly and efficiently. The benefits can be classified under two ways as follows: First, even uncompressed raw images can be stored and transmitted easily. Secondly, compression provides better resources for transmission and storage. Image compression is the representation of image in a digitized form with a few bits maintenance only allowing acceptable level of image quality. Compression addresses the problem of reducing the amount of data required to represent a digital image. A good compression scheme is always composed of many compression methods namely wavelet transformation, predicative coding, and vector quantization and so on. Wavelet transformation is an essential coding technique for both spatial and frequency domains, where it is used to divide the information of an image into approximation and detail sub signals [8]. Artificial Neural Networks (ANN) is also used for image compression. It is a system where many algorithms are used. The ANN is viewed as a graph with various nodes namely source, sink and internal [9]. The input node exists in the input layer and output node exists in the output layer whereas hidden nodes exist in one or more hidden layers.

In ANN various learning method are used namely Unsupervised, Reinforcement learning and Back propagation. Counter Propagation Neural Network (CPN) has become popular since it converges faster. A level of advancement in CPN is forward only Counter Propagation, where correlation based technique is used [10], [11]. Modified forward only Counter Propagation is proposed where distance metrics are used to find the winner among the hidden layers neurons Image compression is used to minimize the size in bytes of a graphics file without degrading the quality of the image. There are two types of image compression is present. They are lossy and lossless. Some of the compression algorithms are used in the earlier days [3] and [4] and it was one of the first to be proposed using wavelet methods [2]. Over the past few years, a variety of powerful and sophisticated wavelet based schemes for image compression have been developed and implemented. The coders provide a better quality in the pictures. Wavelet based image compression based on set partitioning in hierarchical trees (SPIHT) [5] and [6] is a powerful, efficient and yet computationally simple image compression algorithm. It provides a better performance when compared to the Embedded Zero tree wavelet [7] transform.

This paper addresses the following problems: (1) Implementing simple algorithm, (2) obtaining high image quality using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). This is followed by high frequency wavelet coefficients bit stream.

2. Image Compression

Following the rapid development of information and communication technologies, more and more information has to be processed, stored, and transmitted in high speed over networks. The need for data compression and transmission is increasingly becoming a significant topic in all areas of computing and communications. Computing techniques that would considerably reduce the image size that occupies less space and bandwidth for transmission over networks form an active research.

Image compression deals with reducing the amount of data required to represent a digital image [3]. Compression and the amount of distortion in the reconstructed image.

3. Neural Network

Artificial Neural Networks have been applied to many problems, and have demonstrated their superiority over classical methods when dealing with noisy or incomplete data. One such application is for data compression. Neural networks seem to be well suited to this particular function, as they have an ability to pre-process input patterns to produce simpler patterns with fewer components [5]. Neural networks are computer algorithms inspired by the way information is processed in the nervous system. An important difference between neural networks and other AI techniques is their ability to learn. The network “learns” by adjusting the interconnections (called weights) between layers. When the network is adequately trained, it is able to generalize relevant output for a set of input data. A valuable property of

A neural network is that of generalization, whereby a trained neural network is able to provide a correct matching in the form of output data for a set of previously unseen input data. Learning typically occurs by example through training, where the training algorithm iteratively adjusts the connection weights (synapses). Back-propagation (BP) is one of the most famous training algorithms for multilayer perceptrons. Learning algorithms has significant impact on the performance of neural networks, and the effects of this depend on the targeted application. The choice of suitable learning algorithms is therefore application dependent.

4. SPIHT

The different compression methods were developed specifically to achieve at least one of those objectives. What makes SPIHT really outstanding is that it yields all those qualities simultaneously. So, if in the future you find one method that claims to be superior to SPIHT in one evaluation parameter (like PSNR), remember to see who wins in the remaining criteria. SPIHT stands for Set Partitioning in Hierarchical Trees. The term Hierarchical Trees refers to the quad trees that we defined in our discussion of EZW. The SPIHT image coding algorithm was developed in 1996 by Said and Pearlman and is another more efficient implementation of the embedded zerotree wavelet (EZW) [2][8] algorithm by Shapiro. After the wavelet transform is applied to an image, the main algorithm works by partitioning the wavelet decomposed image into significant and insignificant partitions based on the following function. The images obtained with wavelet-based methods yield very good visual quality. At first it was shown that even simple coding methods produced good results when combined with wavelets and is the basis for the most recently JPEG2000 standard. However, SPIHT belongs to the next generation of wavelet encoders, employing more sophisticated coding. In fact, SPIHT exploits the properties of the wavelet-transformed images to increase its efficiency. Our discussion of SPIHT will consist of three parts. We shall refer to it as the Spatial-orientation Tree Wavelet (STW) algorithm. STW is essentially the SPIHT algorithm, the only difference is that SPIHT is slightly more careful in its organization of coding output. Second, we shall describe the SPIHT algorithm. It will be easier to explain SPIHT using the concepts underlying STW. Third, we shall see how well SPIHT compresses images.

The only difference between STW and EZW is that STW uses a different approach to encoding the zero tree information. STW uses a state transition model. From one threshold to the next, the locations of transform values undergo state transitions.

5. Feature of the Algorithm

Now that we have laid the groundwork for the STW algorithm, we can give its full description.

STW encoding

Step 1 Initialize. Choose initial threshold, $T = T_0$, such that *all* transform values satisfy $|w(m)| < T_0$.

Step 2: Update threshold. Let $T_k = T_{k-1}/2$.

Step 3 Apply the back propagation to Train the Network

Step 4 Dominant pass. Use the following procedure to scan through indices in the dominant list (which can change as the procedure is executed).

Do

Get next index m in dominant list Save old state $S_{old} = S(m, T_{k-1})$

Find new state $S_{new} = S(m, Tk)$
 Output code for state transition $Sold \rightarrow S_{new}$
 If $S_{new} \neq Sold$ then do the following
 If $Sold \neq SR$ and $S_{new} \neq IV$ then
 Append index m to refinement list
 Output sign of $w(m)$ and set $wQ(m) = Tk$
 If $Sold = IV$ and $S_{new} = SR$ then
 Append child indices of m to dominant list
 If $S_{new} = SV$ then Remove index m from dominant list

Steps 5 while images feature value get trained.

Step 6: Refinement pass. Scan through indices m in the refinement list found with higher threshold values Tj , for $j < k$ (if $k = 1$ skip this step).
 For each value $w(m)$, do the following:
 If $|w(m)| \square [wQ(m), wQ(m) + Tk]$,
 then
 Output bit 0
 Else if $|w(m)| \square [wQ(m) + Tk, wQ(m) + 2Tk]$, then

Output bit 1
 Replace value of $wQ(m)$ by $wQ(m) + Tk$.

Step 7: Loop. Repeat steps 2 through 4.

We would like the algorithm to have low computational requirements by computing only the required coefficients as opposed to all N^2 coefficients for an $N \times N$ image.

Let us assume that we have decided to have non-zero coefficients in the representation.

It is possible to control both (i) the number of significant coefficients in the representation and (ii) the PSNR. Its performance is comparable to the best available algorithms.

The SPIHT encoding process, as described in [6], is phrased in terms of pixel locations $[i, j]$ rather than indices m in a scan order. To avoid introducing new notation, and to highlight the connections between SPIHT and the other algorithms, EZW and STW, we shall rephrase the description of SPIHT from [6] in term of scanning indices. We shall also slightly modify the notation used in the interests of clarity.

SPIHT keeps track of the states of sets of indices by means of three lists. They are the list of insignificant sets (LIS), the list of insignificant pixels (LIP), and the list of significant pixels (LSP). For each list a set is identified by a single index, in the LIP and LSP these indices represent the singleton sets $\{m\}$ here m is the identifying index. An index m is called either significant or insignificant, depending on whether the transform value $w(m)$ is significant or insignificant with respect to a given threshold. For the LIS, his index m denotes either $D(m)$ or $G(m)$. In the former case, the index m is said to be of type D and, in the latter case, of type G.

Algorithm by Neural Network

1. Choose training pair and copy it to input layer
2. Cycle that pattern through the net
3. Calculate error derivative between output activation and target output
4. Back propagate the summed product of the weights and errors in the output layer to calculate the error on the hidden units
5. Update weights according to the error on that unit Until error is low or the net settles

6. Proposed Work

Our Proposed scheme tells us that we compress the Image with Neural Network and after that we apply different wavelet. So that the compression Ratio, BPP, PSNR and MSE can give the improved Result in compression to previous compression result. The Previous work is in either Image compression through Neural Network, or either

with two wavelets. In this work we are trying to combine the different wavelets and Neural Network to compress better compression of Image result. We apply the wavelets such as EZW, WDR, SPHIT, and STW. The above algorithms finding the parameters As PSNR, CR, BPP and MSE values for the images compressed by SPIHT, EZW and STW. The PSNR, CR, BPP, MSE values are calculated by using the following formula.

MSE is calculated by this formula:

Peak Signal to Noise Ratio (PSNR) is generally used to analyze quality of image, sound and video files in dB (decibels). PSNR calculation of two images, one original and an altered image, describes how far two images are equal.

MSE: Mean-Square error.
x: width of image.
y: height of image.
x*y: number of pixels (or quantities).

The formula for calculating the Peak Signal to noise Ratio is as follows:

$$PSNR(dB) = 10 * \log\left(\frac{255^2}{MSE}\right)$$

$$MSE = \frac{\sum_{i=1}^x \sum_{j=1}^y (A_{ij} - B_{ij})^2}{x * y}$$

These are the result in tables showing Image Size, Compression ratio, BPP, MSE and PNSR

Bits per Pixel

The terminology for image formats can be confusing because there are often several ways of describing the same format. This topic explains what the terms mean.

If an image is 24 bits per pixel, it is also called a 24-bit image, a true color image, or a 16M color image. Sixteen million is roughly the number of different colors that can be represented by 24 bits, where there are 8 bits for each of the red, green, and blue (RGB) values.

A 32-bit image is a specialized true-color format used in image files, where the extra byte carries information that is either converted or ignored when the file is loaded. The extra byte is used for an additional color plane in CMYK files, which are specialized files for color printing. by default, converts the values to 24-bit RGB values when loading the image. The additional byte may also be used for an Alpha channel, which carries extra information such as a transparency indicator.

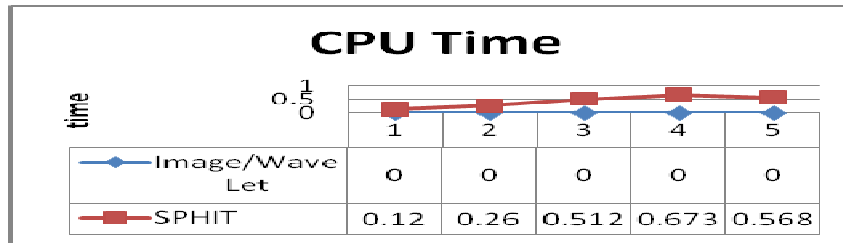
The number of distinct colors that can be represented by a pixel depends on the number of bits per pixel (bpp). A 1 bpp image uses 1-bit for each pixel, so each pixel can be either on or off. Each additional bit doubles the number of colors available, so a 2 bpp image can have 4 colors, and a 3 bpp image can have 8 colors:

- 1 bpp, 2¹ = 2 colors (monochrome)

The compression ratio (that is, the size of the compressed file compared to that of the uncompressed file) of lossy image codecs is nearly always far superior to that of the audio and still-image equivalents.

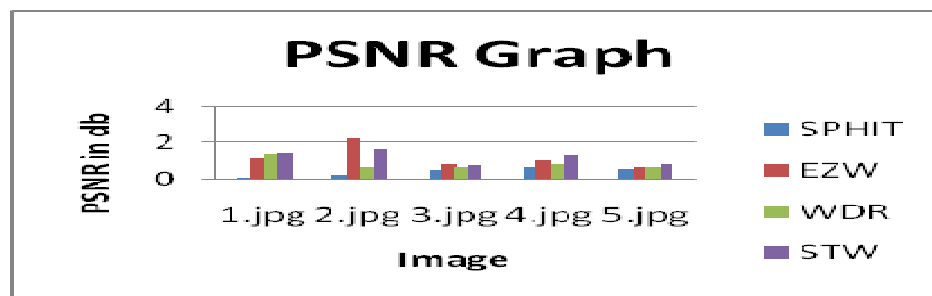
- Video can be compressed immensely (e.g. 100:1) with little visible quality loss
- Audio can often be compressed at 10:1 with imperceptible loss of quality
- Still images are often lossily compressed at 10:1, as with audio, but the quality loss is more noticeable, especially on closer inspection.

The compression rate is 5 to 6 % in lossy compression while in lossless compression it is about 50 to 60 % of the actual file.

Result

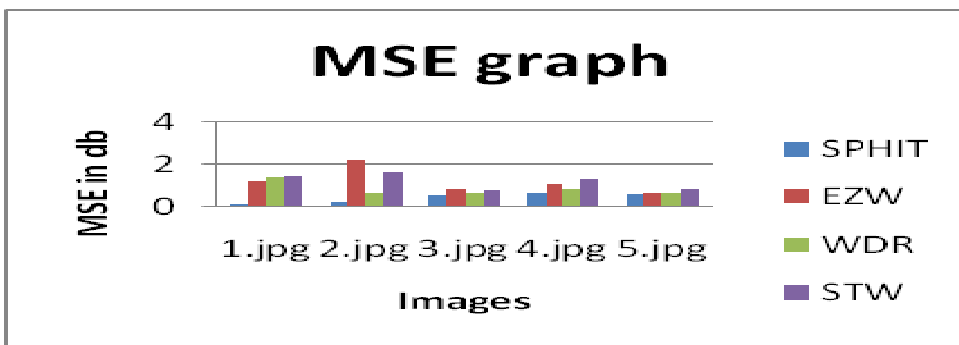
PSNR in db

Image/Wave Let	SPHIT	EZW	WDR	STW
1.jpg	132.3	138.23	136.2	133.66
2.jpg	148.65	156.56	155.33	152.123
3.jpg	145.23	148.65	150.32	146.58
4.jpg	165.36	169.25	166.23	167.58
5.jpg	129.03	135.21	136.32	130.56



MSE

Image/Wave Let	SPHIT	EZW	WDR	STW
1.jpg	23.265	25.321	25.889	25.56
2.jpg	28.325	33.445	31.23	30.50
3.jpg	27.555	30.260	30.5	29.32
4.jpg	30.33	36.32	35.23	33.23
5.jpg	29.03	35.21	36.32	30.56



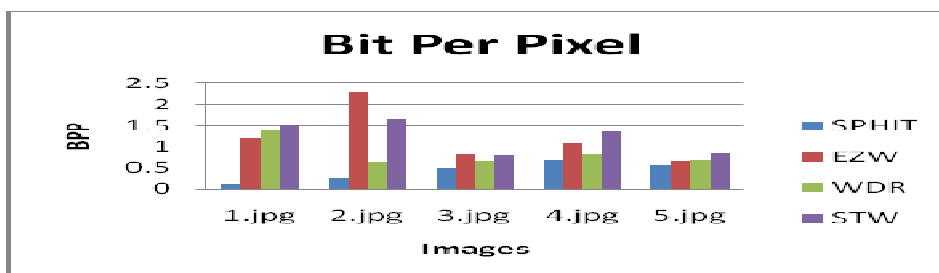
Compression Ratio

Image/Wave Let	SPHIT	EZW	WDR	STW
1.jpg	1.12	2.20	2.42	2.51
2.jpg	2.26	3.29	3.632	4.668
3.jpg	2.56	3.056	3.66	3.212
4.jpg	3.33	6.32	5.23	3.23
5.jpg	6.03	8.21	6.32	7.56



BPP

Image/Wave Let	SPHIT	EZW	WDR	STW
1.jpg	0.12	1.20	1.42	1.51
2.jpg	0.26	2.29	0.632	1.668
3.jpg	0.512	0.81	0.66	0.79
4.jpg	0.673	1.09	0.81	1.35
5.jpg	0.568	0.66	0.68	0.85



4. Conclusion

Authors are expected to conclude their presentation comprehensively in the conclusion. Authors have to freedom to include future research details as part of the conclusion or as a separate section before the conclusion, depending on the appropriateness. Conclusion should not repeat the main text; instead it should try to help the reader to have a strong view on the article's claims. Following a critical approach on own research methods and experiments can show maturity and impartial evaluation, which enhance the quality of your article.

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