

Enhanced Image Compression Using Wavelets

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Abstract— Data compression which can be lossy or lossless is required to decrease the storage requirement and better data transfer rate. One of the best image compression techniques is using wavelet transform. It is comparatively new and has many advantages over others. Wavelet transform uses a large variety of wavelets for decomposition of images. The state of the art coding techniques like HAAR, SPIHT (set partitioning in hierarchical trees) and use the wavelet transform as basic and common step for their own further technical advantages. The wavelet transform results therefore have the importance which is dependent on the type of wavelet used. In our thesis we have used different wavelets to perform the transform of a test image and the results have been discussed and analyzed. Haar, Spilit wavelets have been applied to an image and results have been compared in the form of qualitative and quantitative analysis in terms of PSNR values and compression ratios. Elapsed times for compression of image for different wavelets have also been computed to get the fast image compression method. The analysis has been carried out in terms of PSNR (peak signal to noise ratio) obtained and time taken for decomposition and reconstruction.

Index Terms— Discrete Wavelet Transform, Image Compression Haar wavelet transform lossy compression technique .

I. INTRODUCTION

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 [1]. 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, predictive 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 [2].

Image Compression is an important component of the solutions available for creating image file sizes of manageable and transmittable dimensions. Platform portability and performance are important in the selection of the compression/decompression technique to be employed [3]. Images have considerably higher storage requirement than text; Audio and Video Data require more demanding properties for data storage. An image stored in an uncompressed file format, such as the popular BMP format, can be huge. An image with a pixel resolution of 640 by 480 pixels and 24-bit colour resolution will take up $640 * 480 * 24/8 = 921,600$ bytes in an uncompressed format. The huge amount of storage space is not only the consideration but also the data transmission rates for communication of continuous media are also significantly large. This kind of data transfer rate is not realizable with today's technology, or in near the future with reasonably priced hardware.

Image compression addresses the problem of reducing the amount of data required to represent a digital image. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. Compression is achieved by the removal of one or more of the three basic data redundancies:

1. Coding Redundancy
2. Inter-pixel Redundancy
3. Psych-visual Redundancy

II. IMAGE COMPRESSION PRINCIPLES

Image compression reduces the number of bits required to represent the image, therefore the amount of memory required to store the data set is reduced. It also reduces the amount of time required to transmit a data set over a communication link at a given rate. Different methods are developed to perform the image compression.

The compression ratio is one of the quantitative parameters to measure the performance of compression methods. Compression ratio is defined as ratio of the size of original data set to the size of the compressed data set. There are various methods of compressing still images, but every method has three basic steps involved in any of the data compression scheme: Transformation, reduced precision (quantization or thresholding), and minimization of number of bits to represent the image(encoding). The basic block diagram of compression scheme is shown in Fig.1.

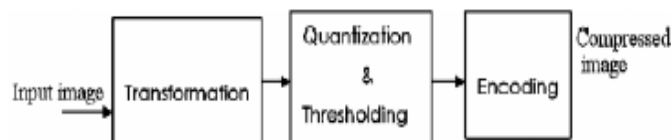


Figure1: The Block Diagram of Compression Scheme

2.1. Transformation

For image compression, it is desirable that the selection of transform should reduce the size of resultant data set as compared to source data set. Few transformations reduce the number of data items in the data set. Few transformations reduce the numerical size of the data items that allows them to represent by the fewer binary bits. In data compression, transform is intended to decorrelate the input signals by transformation. The data represented in the new system has properties that facilitate the compression. Some mathematical transformations have been invented for the sole purpose of data compression; selection of proper transform is one of the important factors in data compression scheme. It still remains an active field of research. The technical name given to these processes of transformation is mapping. Some mathematical transformations have been invented for the sole purpose of data compression, other have been borrowed from various applications and applied to data compression.

2.2. Quantization/Thresholding

In the process of quantization each sample is scaled by the quantization factor. Where as in the process of thresholding the samples are eliminated if the value of sample is less than the defined threshold value. These two methods are responsible for introduction of error and it leads in degrading the quality. The degradation is based on selection of quantization factor and threshold value. For the high value of threshold the loss of information is more, and for low value of threshold the loss of information is less. By considering the resultant loss of information, the selection of threshold should be low, but for the low value of the threshold there is negligible compression of data. Hence quantization factor, or threshold value should be selected in such a way that it should satisfy the constraints of human visual system for better visual quality, and high compression ratio. Human Visual System is less sensitive to high frequency signal and more sensitive to low frequency signal. By considering this phenomenon, the threshold value or quantization factor is selected and thresholding/ quantization take place in image compression.

2.3. Encoding

This phase of compression reduces the overall number of bits needed to represent the data set. An entropy encoder further compresses the quantized values to give better overall compression. This process removes the redundancy in the form of repetitive bit patterns in the output of quantizer. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than most commonly used entropy encoders.

III. LITERATURE REVIEW

“Ming Yang & Nikolaos Bourbakis (2005) et al. [3] discussed the objective of compression is to reduce the number of its as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible. Image compression systems are composed of two distinct structural blocks: an encoder and a decoder [3], [4].

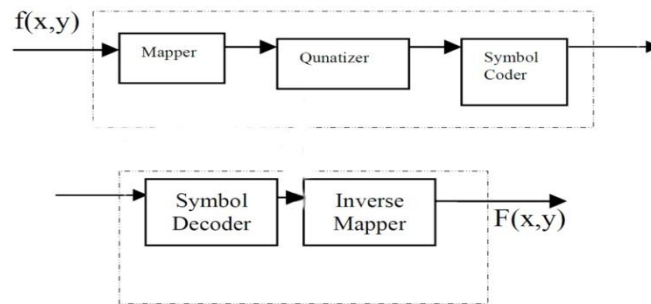


Figure 2 Image compression encoder and decoder

The image compression techniques are broadly classified into two categories depending whether or not an exact replica of the original image could be reconstructed using the compressed image [5]. These are:

1. Lossless technique: Lossless coding guarantees that the decompressed image is absolutely identical to the image before compression. This is an important requirement for some application domains, e.g. Medical Imaging, where not only high quality is in the demand, but unaltered archiving is a legal requirement. Lossless techniques can also be used for the compression of other data types where loss of information is not acceptable, e.g. text documents and program executable.

2. Lossy technique: Lossy compression contains degradation relative to the original. Often this is because the compression schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually Lossless).

Chui, Charles (1992) et al. [6] discusses the similarities and dissimilarities between Fourier and Wavelet transform. The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are both linear operations and the mathematical properties of the matrices involved in the transforms are similar as well. The inverse transform matrix for both the FFT and the DWT is the transpose of the original. As a result, both transforms can be viewed as a rotation in function space to a different domain. For the FFT, this new domain contains basis functions that are sine's and cosines. For the wavelet transform, this new domain contains more complicated basis functions called wavelets, mother wavelets, or analysing wavelets. Both transforms have another similarity. The basis functions are localized in frequency, making mathematical tools such as power spectra (how much power is contained in a frequency interval) and scale grams (to be defined later) useful at picking out frequencies and calculating power distributions. The most interesting dissimilarity between these two kinds of transforms is that individual wavelet functions are *localized in space*. Fourier sine and cosine functions are not. This localization feature, along with wavelets' localization of frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features in images, and removing noise.

Jun Wang and H. K. Huang(1996) et al. [7] proposes a three-dimensional (3-D) medical image compression method for computed tomography (CT) and magnetic resonance (MR) that uses a separable non-uniform 3-D wavelet transform. The separable wavelet transform employs one filter bank within two-dimensional (2-D) slices and then a second filter bank on the slice direction. CT and MR image sets normally have different resolutions within a slice and between slices. The pixel distances within a slice are normally less than 1 mm and the distance between slices can vary from 1 mm to 10 mm. To find the best filter bank in the slice direction author uses the various filter banks in the slice direction and compare the compression results. The results from the 12 selected MR and CT image sets at various slice thickness show that the Haar transform in the slice direction gives the optimum performance for most image sets, except for a CT image set which has 1 mm slice distance. Compared with 2-D wavelet compression, compression ratios of the 3-D method are about 70% higher for CT and 35% higher for MR image sets at a peak signal to noise ratio (PSNR) of 50 dB. In general, the smaller the slice distances, the better the 3-D compression performance. The decompressed image quality is measured by the peak signal-to-noise ratio (PSNR) defined as

$$\text{PSNR} = 20 \log \frac{f_{\max}}{\left\{ \frac{\sum [f(x, y, z) - f_c(x, y, z)]^2}{N} \right\}^{1/2}}$$

where f_{\max} is the maximum gray level of the image set, N is total number of pixels, $f(x, y, z)$ is the original image, and $f_c(x, y, z)$ is the decompressed image. The denominator is the root mean square (rms) error of the decompressed image. The larger the PSNR, the better the decompressed image quality is. The compression performance is measured by compression ratio (CR) which is defined as

$$CR = \frac{\text{Original bits per pixel}}{\text{Compressed bits per pixel}}$$

The image sets were also compressed with the 3-D wavelet compression method and a 2-D wavelet compression method. In the 3-D compression method, the Haar filter was used in the z direction. The 2-D compression algorithm was similar to the 3-D compression algorithm except that a 2-D wavelet transform was applied to each slice. Multiple slices are simply compressed slice by slice with the 2-D method and the final compression ratio is obtained by averaging whole set of 3-D data.

Colm Mulcahy (1997) et al. [8] gives a brief introduction to the subject by showing how the Haar wavelet transform allows information to be encoded according to "levels of detail." Author uses the Haar wavelet transform and explains how it can be used to produce images. Matlab numerical and visualization software was used to perform all of the calculations and generate and display all of the pictures. they describe a scheme for transforming such large arrays of numbers into arrays that can be stored and transmitted more efficiently; the original images (or good approximations of them) can then be reconstructed by a computer with relatively little effort. Author demonstrated how to wavelet transform a matrix describing a method for transforming strings of data called averaging and differencing. The technique to transform an entire matrix as follows: Treat each row as a string, and perform the averaging and differencing on each one to obtain a new matrix, and then apply exactly the same steps on each column of this new matrix, finally obtaining a row and column transformed matrix. It was concluded that wavelets provide an alternative to classical Fourier methods for both one- and multi-dimensional data analysis and synthesis, and have numerous applications both within mathematics (e.g., to partial differential operators) and in areas as diverse as physics, seismology, medical imaging, digital image processing, signal processing, and computer graphics and video. Unlike their Fourier cousins, wavelet methods make no assumptions concerning periodicity of the data at hand.

Vinay U. Kale & Nikkoo N. (2010) et al. [9] explains Discrete Cosine Transform, Discrete Wavelet Transform. The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain. The discrete wavelet transform (DWT) refers to wavelet transforms for which the wavelets are discretely sampled. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix. Most notably, the discrete wavelet transform is used for signal coding, where the properties of the transform are exploited to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. It was also concluded that the human eye is fairly good at seeing small differences in brightness over a relatively large area, but not so good at distinguishing the exact strength of a high frequency brightness variation. This fact allows one to get away with greatly reducing the amount of information in the high frequency components. This is done by simply dividing each component in the frequency domain by a constant for that component, and then rounding to the nearest integer. This is the main lossy operation in the whole process. As a result of this, it is typically the case that many of the higher frequency components are rounded to zero, and many of the rest become small positive or negative numbers.

IV. HAAR WAVELET TRANSFORM

Alfred Haar (1885-1933) was a Hungarian mathematician who worked in analysis studying orthogonal systems of functions, partial differential equations, Chebyshev approximations and linear inequalities. In 1909 Haar introduced the Haar wavelet theory. A Haar wavelet is the simplest type of wavelet. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform..

The mathematical prerequisites will be kept to a minimum; indeed, the main concepts can be understood in terms of addition, subtraction and division by two. We also present a linear algebra implementation of the Haar wavelet transform, and mention important recent generalizations.

Like all wavelet transforms, the Haar transform decomposes a discrete signal into two subsignals of half its length. The Haar wavelet transform has a number of advantages:

- It is conceptually simple and fast
- It is memory efficient, since it can be calculated in place without a temporary array.
- It is exactly reversible without the edge effects that are a problem with other wavelet transforms.
- It provides high compression ratio and high PSNR (Peak signal to noise ratio).
- It increases detail in a recursive manner.

The Haar Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation.

Data compression in multimedia applications has become more vital lately where compression methods are being rapidly developed to compress large data files such as images. Efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size.

Visual inspection and observation by humans is an empirical analysis that involves a number of people who observe the smoothness and edge continuity of certain objects within reconstructed images and then decide which compression ratio provides a compromise between high compression ratio and minimal loss of quality.

The aim of this paper is to give brief introduction to the subject by showing how the Haar wavelet transform allows information to be encoded according to "levels of detail." In one sense, this parallels the way in which we often process information in our everyday lives. Our investigations enable us to give two interesting applications of wavelet methods to digital images: compression and progressive transmission.

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V. SPIHT

SPIHT is a wavelet-based image compression coder. It first converts the image into its wavelet transform and then transmits information about the wavelet coefficients. The decoder uses the received signal to reconstruct the wavelet and performs an inverse transform to recover the image. We selected SPIHT because SPIHT and its predecessor, the embedded zerotree wavelet coder, were significant breakthroughs in still image compression in that they offered significantly improved quality over vector quantization, JPEG, and wavelets combined with quantization, while not requiring training and producing an embedded bit stream. SPIHT displays exceptional characteristics over several properties

all at once [12] including:

- Good image quality with a high PSNR
- Fast coding and decoding
- A fully progressive bit-stream
- Can be used for lossless compression
- May be combined with error protection
- Ability to code for exact bit rate or PSNR

The Discrete Wavelet Transform (DWT) runs a high and low-pass filter over the signal in one dimension. The result is a new image comprising of a high and low-pass subband. This procedure is then repeated in the other dimension yielding four subbands, three high-pass components and one lowpass component. The next wavelet level is calculated by repeating the horizontal and vertical transformations on the low-pass subband from the previous level. The DWT repeats this procedure for however many levels are required. Each procedure is fully reversible (within the limits of fixed precision) so that the original image can be reconstructed from the wavelet transformed image.

SPIHT is a method of coding and decoding the wavelet transform of an image. By coding and transmitting information about the wavelet coefficients, it is possible for a decoder to perform an inverse transformation on the wavelet and reconstruct the original image. The entire wavelet transform does not need to be transmitted in order to recover the image. Instead, as the decoder receives more information about the original wavelet transform, the inverse-transformation will yield a better quality reconstruction (i.e. higher peak signal to noise ratio) of the original image.

SPIHT generates excellent image quality and performance due to several properties of the coding algorithm. They are partial ordering by coefficient value, taking advantage of redundancies between different wavelet scales and transmitting data in bit plane order [13].

Following a wavelet transformation, SPIHT divides the wavelet into *Spatial Orientation Trees*. Each node in the tree corresponds to an individual pixel.

The offspring of a pixel are the four pixels in the same spatial location of the same subband at the next finer scale of the wavelet. Pixels at the finest scale of the wavelet are the leaves of the tree and have no children. Every pixel is part of a 2 x 2 block with its adjacent pixels. Blocks are a natural result of the hierarchical trees because every pixel in a block shares the same parent. Also, the upper left pixel of each 2 x 2 block at the root of the tree has no children since there only 3 subbands at each scale and not four. Figure 3 shows how the pyramid is defined. Arrows point to the offspring of an individual pixel, and the grayed blocks show all of the descendants for a specific pixel at every scale.

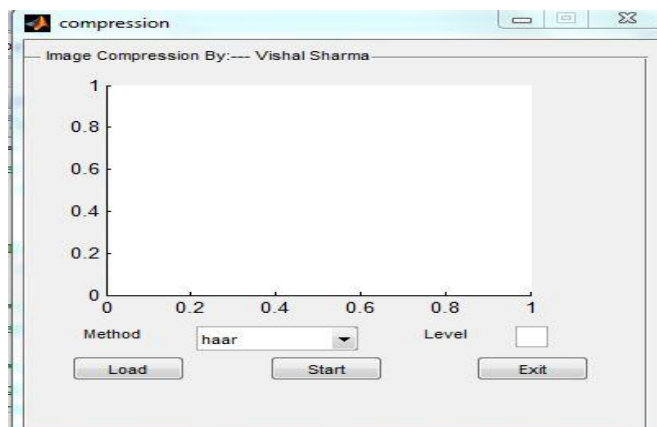


Figure3 the basic layout of the proposed system

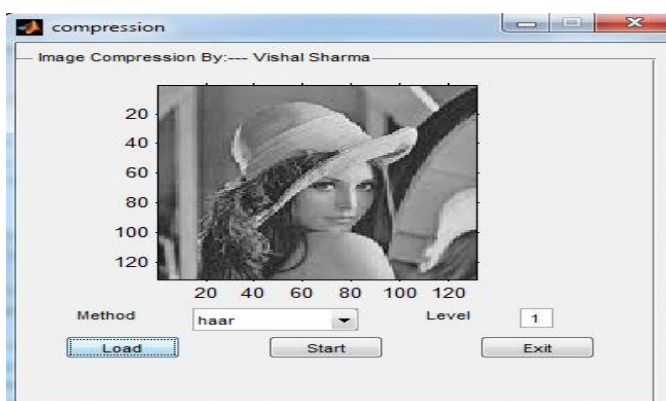


Figure 4. the input image is loaded.

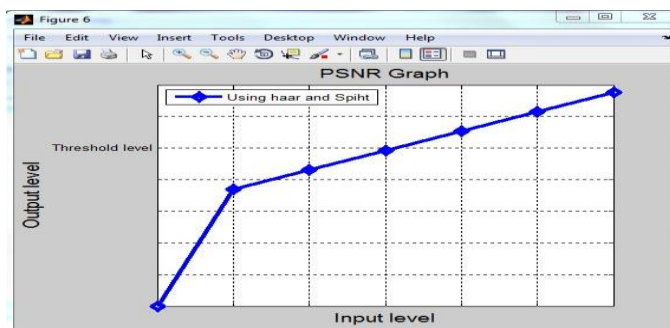


figure5 The output graph.

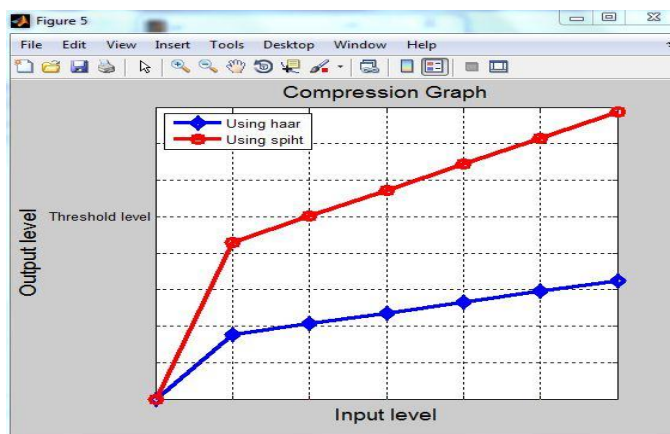


Figure6 the output graph using Haar and Spht.

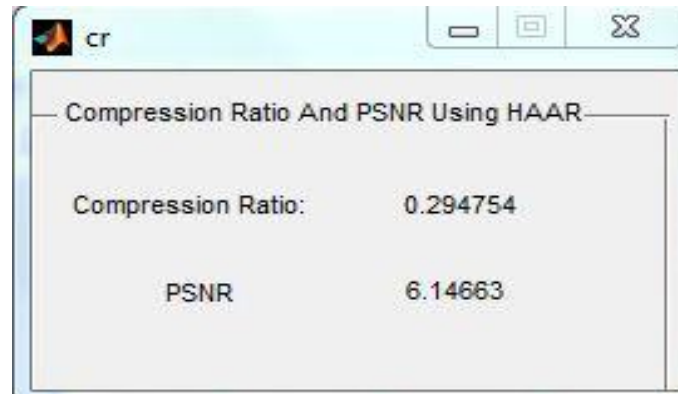


Figure 7. The compression ratio and the PSNR using Haar.

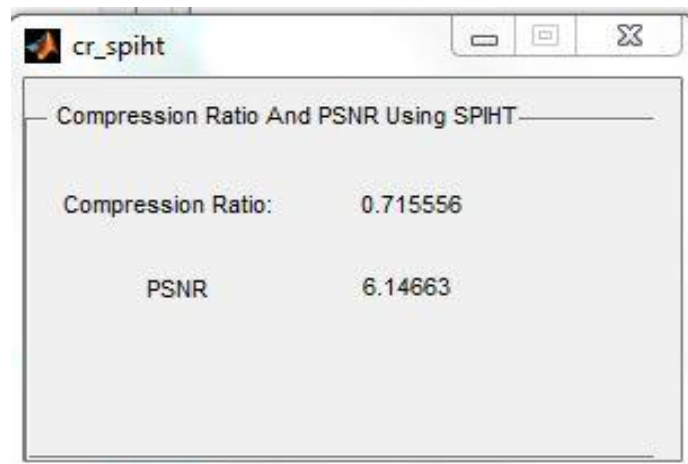


Figure 8 the compression ratio and PSNR using Haar and Spiht.



Figure 9 the final compressed image.

VI. CONCLUSION

This paper reported is aimed at developing computationally efficient and effective algorithm for lossy image compression using wavelet techniques. So this proposed algorithm developed to compress the image so fastly. The promising results obtained concerning reconstructed image quality as well as preservation of significant image details, while on the other hand achieving high compression rates.

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