Parameters Affecting the Compression of Images using Wavelet Transform

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Abstract- The wavelet transform is a key processing mechanism that mainly used for the compression of the images and multimedia files. In modern era, the discrete wavelet transform has emerged as a conventional technique for the image compression. The technological advances escort a high demand for the large capacities, high performance devices, and high bandwidths because of an increment in the sizes of the images. It becomes necessary to use an image compression technique for diminishing the computational, transmittal, storage costs and analyze many images. Because of this uniqueness, in this technique the images are getting compressed by storing only the significant information that is required for reconstructing the image. This paper reviews the parameters that persuade the compression of numerous images using the wavelet transform.

Keywords – Compression, multi-resolution, Synthetic, Natural Images, Decomposition entropy ,energy retention.

I. INTRODUCTION

The transform-based wavelet transform, is now making it even easier to compress, transmit, and analyse many images. Unlike the Fourier transform, whose basis functions are sinusoids, wavelet transforms are based on small waves, called wavelets, of varying frequency and limited duration Wavelets are the foundation for representing images in various degrees of resolution. Conventional Fourier transforms, on the other hand, provide only the notes or frequency information while the temporal information is lost in the transformation process. To explain the parameters which influence the compression of images here two images fig.1 and fig.2 i.e. synthetic image(image with enhancement ex. Image capture using camera) and natural image(image without enhancement) respectively are consider.

Figure1. Sketch-pens (Synthetic Image)

Figure.2 Green shrub (Natural Image)

Image compression is extremely important for efficient transmission and storage of this image. With the use of digital cameras, requirements for storage, manipulation, and transfer of digital images have grown rapidly. These image files can be very large and can occupy a significant memory space. A grey scale image comprising 256 x 256 pixels requires 65, 536 elements to store, similarly a typical 640 x 480 color image requires nearly a millions therefore, downloading of these files from internet can be very time consuming task. Image data comprise of a significant portion of the multimedia data and they occupy the major portion of the communication bandwidth for multimedia communication. It is therefore crucial to develop competent techniques for image compression [5].A common characteristic of most of the images is that the neighboring pixels are correlated and therefore contain redundant information. Redundancy reduction aims at removing duplication from the signal source. Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver ,namely the Human Visual System [10].In digital signal processing, three types of redundancy can be identified 1.Spatial Redundancy or correlation between neighboring pixel values 2.Spectral Redundancy or correlation between different color planes or spectral bands 3.Temporal Redundancy or correlation between adjacent frames in a sequence of images[9].Most of the current methods of image compression are transform based methods such as DCT or DWT. The transform based compression has become the standard paradigm in image compression such as JPEG and in video compression such as MPEG-2 and H.263 where the Discrete Cosine Transform (DCT) is used because of its de-correlation and energy compaction properties. In the case of DCT based image compression, image is divided into blocks of uniform size. But, the block-based segmentation of source image has a fundamental limitation of the DCT based compression system. The degradation is known as the “blocking effect” and depends on block size. Wavelets provide good compression ratios [12], especially for high resolution images.

Wavelets perform much better than competing technologies like JPEG, both in terms of signal-to-noise ratio individual quality. Unlike JPEG, it shows no blocking effect but allow for a graceful degradation of the whole image quality, while preserving the important details of the image. Recently, Discrete Wavelet Transform (DWT) has emerged as a popular technique for image compression applications with excellent compression performance. In DWT the image is transformed and compressed as a single data object rather than block by block. This technique allows a uniform distribution of compression error across entire image. Discrete wavelet transform have higher de-correlation and frequency, gives it potentiality for good representation of image with fewer coefficients [14]. The basic measure of the performance of a compression algorithm is the compression ratio, which is defined by the ratio between original data size and compressed data size. Higher compression ratios will produce lower image quality and the vice versa is also true [4].

II. LITERATURE REVIEW

Vast research has been done on image compression using different transforms because images contain large amount of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore it is advantageous to compress the image by storing only the essential information needed to reconstruct the image. Wavelets are mathematical functions in which data should be divided into different frequency components and then matched the resolution into its scale. Wavelet transforms change a signal into a series of wavelets. In Wavelet Image Processing a single image can store different parts of resolutions, which should be divided into many parts. Wavelet is applicable for compressing the image using less storage space and also containing the full details of the image. An image can be decomposed into approximate, horizontal, vertical and diagonal details. Joseph Fourier discovered sine's and cosines that are used to symbolize the approximation functions of an image and these functions are non-local functions. Scale used to represent data, which play important role in wavelet analysis and wavelet algorithms method representing at diverse scales or different resolutions. If window should be large it provides large features and if window should be small it provides minor features. Wavelets are right for estimating data with sharp breaks. The wavelet analysis determines wavelet prototype function that is known as analyzing wavelet [15].

For image coding, a number of reversible integer-to-integer wavelet transforms are compared on the basis of their lossy compression performance, lossless compression performance, and computational complexity. Reversible integer-to-integer versions of numerous transforms are also compared to their conventional (i.e., nonreversible real-to-real) counterparts for lossy compression. At low bit rates, reversible integer-to-integer and conventional versions of transforms were found to often yield results of comparable quality. Factors affecting the compression performance of reversible integer-to-integer wavelet transforms are also presented, supported by both experimental data and theoretical arguments [16]. Motivated by error concealment applications, this letter proposes a method for the post processing of JPEG-2000 compressed images at very low bitrates. The proposed method counter intuitively employs further compression to achieve image enhancement. This approach, although not widely known, is not entirely new: it is an adaptation of a technique originally designed for the removal of block-transform coding artifacts. The contribution of this work is to demonstrate its applicability to wavelet coders. In its simplest form, this algorithm uses existing system components with little or no additional hardware or software. Experimental results show a distinct reduction of ringing artifacts at very low bitrates [17].

A. Need of wavelet transform –

Wavelet transform is an efficient tool to represent an image. The wavelet transform allows multi-resolution analysis of an image. From many years Fourier transform is a powerful tool that has been available for analysis of signal .Fourier transform gives the information only regarding the frequency content of the signals ,the problem with the Fourier transform is that the frequency analysis cannot offer both good frequency and time resolution at the same time .Fourier transform does not give the information about the time at which particular frequency has occurred in a signal .Hence Fourier transform is not an effective tool to analyse non-stationary signals. To overcome this problem windowed FT or short time FT was introduced, though it provides the time information, multi-resolution is not possible with short time FT .Hence wavelet transform became a answer which localize the signal in both time and frequency domain also allows multi-resolution analysis of an image. Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [11]. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts of an image (scaling function). Fig. 3 shows two waveforms of a family discovered in the late 1980s by Daubechies: the right one can be used to represent detailed parts of the image and the left one to represent smooth parts of the image. The two waveforms are translated and scaled on the time axis to produce a set of wavelet functions at different locations and on different scales. Each wavelet contains the same number of cycles, such that, as the frequency reduces, the wavelet gets longer. High frequencies are transformed with short functions (low scale). Low frequencies are transformed with long functions (high scale). During computation, the analyzing wavelet is shifted over the full domain of the analyzed function. The result of WT is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scal

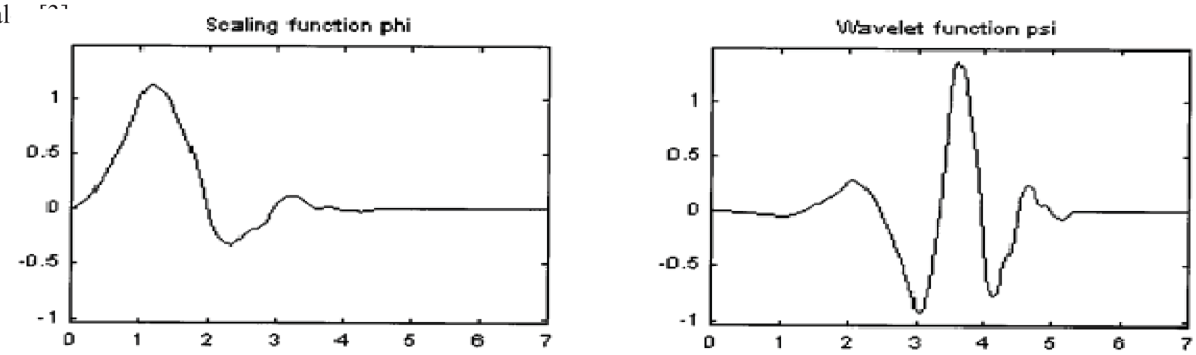

Figure 1. Scaling and Wavelet Function

A. PARAMETER INFLUENCING IMAGE COMPRESSION –

The wavelet chosen as the basis of the forward and inverse transforms as shown below in fig.4 affects all aspects of wavelet coding system design and performance.

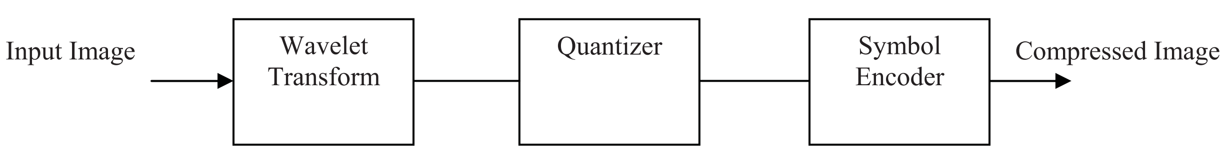

Figure (a)Encoder

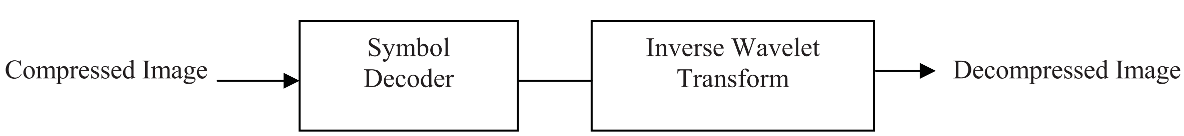

Figure (b) decoder

Figure 2. A wavelet coding system

They impact directly the computational complexity of the transform and less directly the system's ability to compress and reconstruct image of acceptable error. When the transforming wavelet has a companion scaling function, the transformation can be implemented as a sequence of digital filtering operations with no. of filter taps equal no. of nonzero wavelet and scaling vector coefficients. The ability the wavelet to pack the information into small no. of transform coefficient determines its compression and reconstruction performance. The most widely used expansion function for wavelet based compression is the Daubechies wavelet and biorthogonal wavelet[2]. Paper discusses, the different types of wavelet families are examined: Haar Wavelet (HW),Daubechies Wavelet (DW), Coiflet Wavelet (CW), and Biorthogonal Wavelet (BW), Reverse biorthogonal, Symlet (sym3) & Demeyer (dmey). Each wavelet family can be parameterized by N integer that determines filter order. Biorthogonal wavelets can use filters with similar or dissimilar orders for decomposition (Nd) and reconstruction (Nr). In our examples, different filter orders are used inside each wavelet family. We have used the following sets of wavelets: DW- N with N= 1,2,3,4,5,6, CW-N with N=1,2,3,4 , and BW-N with N=1,2,3. Daubechies and Coiflet wavelets are families of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters and, thus, lead to efficient implementation. Only ideal filters with infinite duration can provide alias-free frequency split and perfect interband decorrelation of coefficients. Since time localization of [the filter is very important in visual signal processing, arbitrarily long filters cannot be used. A major disadvantage of DW and CW is their asymmetry, which can cause artifacts at borders of the wavelet subbands. DW is asymmetrical while CW is almost symmetrical. Symmetry in wavelets can be obtained only if we are willing to give up either compact support ororthogonality of wavelet (except for HW, which is orthogonal, compactly supported, and symmetric). If we want both symmetry and compact support in wavelets, we should relax the orthogonality condition and allow nonorthogonal wavelet functions. An example is the family of biorthogonal wavelets that contains compactly supported and symmetric wavelets [4].

B. *Decomposition Level Selections-*

Another factor affecting wavelet coding computational complexity and reconstruction error is number of transform decomposition levels. Because a p-scale fast wavelet transform involves p-filter bank iterations, the number of operations in the computation of forward and inverse increases with the number of decomposition levels [2].The wavelet transform is used to hierarchically decompose the host image into a series of successively lower resolution reference images and their associated detail images. At each level, the low resolution image and the detail images contain the information needed to reconstruct the reference image at the next higher resolution level [1].The human visual system performs similar image decomposition as the wavelet transform in its early processing. The wavelet transform effectively eliminates the blocking effect as its bases overlap one another in the adjacent blocks. It also fundamentally resolves 'corona effect' noise because of narrower high frequency bases [6].The quality of compressed image depends on the number of decompositions (N). The number of decompositions determines the resolution of the lowest level in wavelet domain. If we use larger number of decompositions, we will be more successful in resolving important DWT coefficients from less important coefficients. The HVS is less sensitive to removal of smaller details. After decomposing the image and representing it with wavelet coefficients, compression can be performed by ignoring all coefficients below some threshold. In our experiment, compression is obtained by wavelet coefficient thresholding using a global positive threshold value. All coefficients below some threshold are neglected and compression ratio is computed. Compression algorithm provides two modes of operation:

1) Compression ratio is fixed to the required level and threshold value has been changed to achieve required compression ratio; after that, PSNR is computed.

2) PSNR is fixed to the required level and threshold values have been changed to achieve required PSNR; after that, CR is computed Fig.5 shows comparison of reconstructed image Lena (256 256 pixels, 8 bit/pixel) for 1, 2, 3, and 4 decompositions (CR 50: 1). In this example, DW-5 is used. It can be seen that image quality is better for a large number of decompositions. On the other hand, a larger number of decompositions cause the loss of the coding algorithm efficiency. Therefore, adaptive decomposition is required to achieve balance between image quality and computational complexity. PSNR tends to saturate for a larger number of decompositions. For each compression ratio, the PSNR characteristic has "threshold" which represents the optimal number of decompositions. Below and above the threshold value, PSNR get decreases. For DW-5 used in this example optimal number of decompositions is 5 .The optimal numbers of decompositions depends on filter order. Fig. 6 shows PSNR values for different filter orders and fixed compression ratio (10: 1). It can be seen that as the number of decompositions increases, PSNR is increased up to some number of decompositions. Beyond that, increasing the number of decompositions has a

negative effect. Higher filter order [for example, DW-10 in Fig.6] does not imply better image quality because of the filter length, which becomes the limiting factor for decomposition. Decisions about the filter order and number of decompositions are a matter of compromise. Higher order filters give broader function in the time domain. On the other hand, the number of decompositions determines the resolution of the lowest level in wavelet domain. If the order of function gives a time window of function larger than the time interval needed for analysis of lowest level, the picture quality can only degrade [4].

Figure 5. Reconstructed image Lena; DW-5; CR = 50 : 1. (a) J = 1 (PSNR = 8.40 dB).

(b) J = 2 (PSNR = 11.76 dB). (c) J = 3 (PSNR = 23.39 dB). (d) J = 4 (PSNR = 24.40 dB).

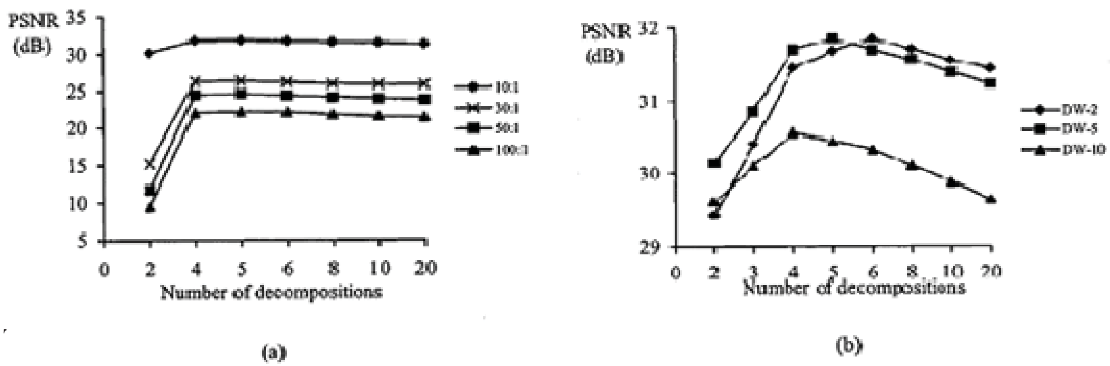

Figure 4. (a & b) PSNR for different number of decompositions (a) DW-5. (b) CR = 10: 1. (b) BJUT watermark Image

C. *Effect on Energy Retention-*

Wavelet analysis can be used to divide the information of an image into approximation and detail sub-signals. The approximation sub-signal shows the general trend of pixel values, and three detail sub-signals show the vertical, horizontal and diagonal details or changes in the image. If these details are comparatively insignificant then they can be set to zero without significantly changing the image quality. The value below which the details are considered to be small enough to be set to zero is known as the threshold.

The greater the number of zeros the greater the compression that can be achieved. The amount of information retained by an image after compression and decompression is known as the energy retained and this is proportional to the sum of the squares of the pixel values. If the energy retained is 100% then the compression is known as lossless , as the image can be reconstructed in the original form. This occurs when the threshold value is set to zero, meaning that no detail been changed. If any value is changed then energy will be lost and this is known as lossy compression. Ideally, during compression the number of zeros and the energy retention will be as high as possible. However, as more zeros are obtained more energy is lost, so a balance between these two needs to be found. The wavelet transform has high de-correlation and energy compaction efficiency [7].Higher filter orders give wider functions in the time domain with higher degree of smoothness. Filter with a high order can be designed to have good frequency localization, which increases the energy compaction. Wavelet smoothness also increases with its order. Filters with lower order have a better time localization and preserve important edge information. Wavelet-based image compression prefers smooth functions (that can be achieved using long filters) but complexity of calculating DWT increases by increasing the filter length. Therefore, in image compression application we have to find balance between filter length, degree of smoothness, and computational complexity. Inside each wavelet family, we can find wavelet function that represents optimal solution related to filter length and degree of smoothness, but this solution depends on image content [3].

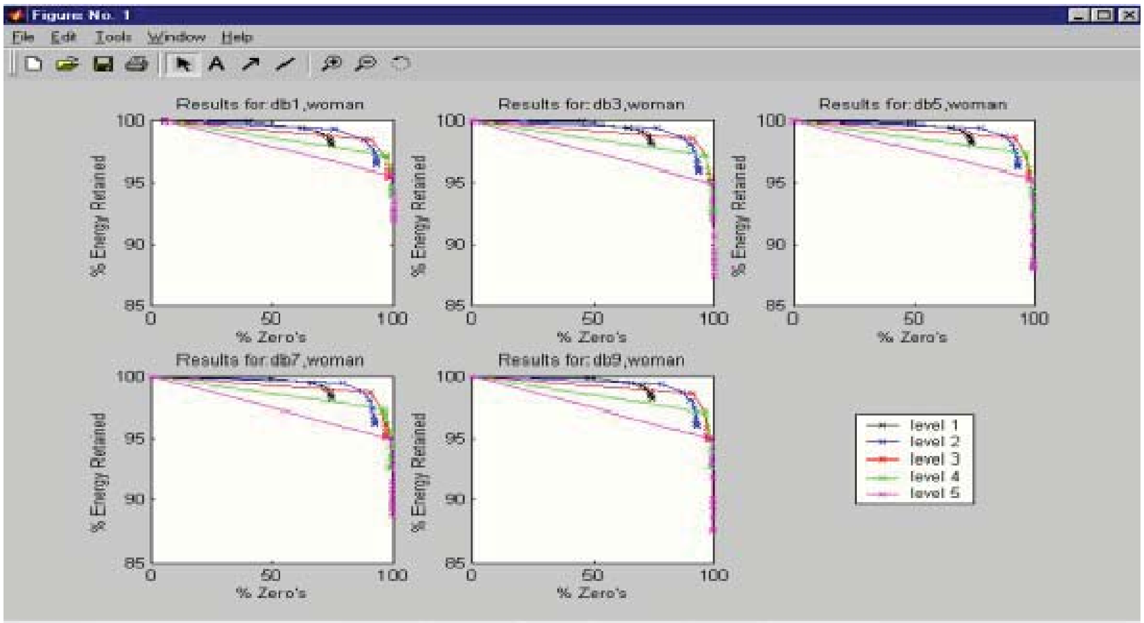

Figure 4. Original Relationship between % of zeros & energy retention with decomposition image

After analysing the graphs it could be seen that at higher decomposition levels
1. The percentage of zeros at 100% energy retention was higher. This suggested a better compression rate had been gained by simply analysing at a deeper level without the need for thresholding (as this point corresponds to a global threshold of 0).
2. The end point was at a higher percentage of zeros but lower energy retained. This suggested that more compression was obtained by decomposing an image to greater levels but by doing so much energy was lost
3. The gradient is steeper at higher levels, suggesting that more energy is lost for every % compression gained [4].

E *Quantizer Design-*

The most important factor affecting the wavelet coding compression and reconstruction error is coefficient quantization. Most of the quantizers are uniform but still effectiveness of quantization can be improved significantly by
1) Introducing the larger quantization interval around zero, called zone or
2) Adapting the size of quantization interval from scale to scale
The selected quantization intervals must be transmitted to decoder with the encoded image bit stream. Based on the image being compressed the intervals computed automatically. For example a global coefficient threshold could computed as median of the absolute values of the first level detail coefficients or as function of number of zeros that are truncated and the amount of energy that is retained in the reconstructed image [2].

F *Entropy-*

Discrete Wavelet Transform (DWT) has emerged as a popular technique for image coding applications. DWT has high decorrelation and energy compaction efficiency. The blocking artifacts and mosquito noise are absent in a wavelet-base decoder due to the overlapping basis functions. The JPEG 2000 standard employs a discrete wavelet transform for image compression due to its merits in terms of scalability, localization and energy concentration [13].The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet analysis, a image 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. In wavelet packet analysis, the details as well as the approximations can be split. This yields more than different ways to encode the image. This is the wavelet packet decomposition tree [8]. If an image has intensity values in the range 0-255 then its bit rate is 8, as the range of 256 values can be represented by binary numbers of length 8. This concept is important in considering compression, for example the green shrub image had only values 0 and 1 so this only requires a bit rate of 1. Having only small values is a great advantage when trying to encode information using Huffman encoding, so this is already, in a sense, compressed because of it range of intensity values without the need for wavelets and thresholding to make the values any smaller. A concept which does take into account this bit rate is the redundancy of the image. If an image has a high redundancy this means that there is much information given in an image that is not required in order to reconstruct the image. The calculation for this is: r = b .He where b is the bit rate and He is the image entropy. Another value that can be calculated is the compression ratio, K, which should give an idea of how compressible the image is given the entropy and bit rate: K = b / He [4].

IV.CONCLUSION

In this paper, we discussed various parameters affecting the compression and reconstruction of numerous images using wavelet transform. The intensive results show that, the different factors such as image content, quantizer design, thresholding , decomposition level and entropy affect the compression to a substantial extent. Selection of these factors may enhance the compression percentage appreciably.

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