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Image Compression Using DCT and Wavelet Transformations

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Abstract

Image compression is a widely addressed researched area. Many compression standards are in place. But still here there is a scope for high compression with quality reconstruction. The JPEG standard makes use of Discrete Cosine Transform (DCT) for compression. The introduction of the wavelets gave a different dimensions to the compression. This paper aims at the analysis of compression using DCT and Wavelet transform by selecting proper threshold method, better result for PSNR have been obtained. Extensive experimentation has been carried out to arrive at the conclusion.

Keywords:*. Discrete Cosine Transform, Wavelet transform, PSNR, Image compression*

1. Introduction

Compressing an image is significantly different than compressing raw binary data. Of course, general purpose compression programs can be used to compress images, but the result is less than optimal. This is because images have certain statistical properties which can be exploited by encoders specifically designed for them. Also, some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space. This also means that lossy compression techniques can be used in this area. 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.For still image compression, the `Joint Photographic Experts Group' or JPEG standard has been established by ISO (International Standards Organization) and IEC (International Electro-Technical Commission). The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) scheme. More recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios.Over the past few years, a variety of powerful and sophisticated wavelet-based schemes for image compression have been developed and implemented. Because of the many advantages, the top contenders in the upcoming JPEG-2000 standard are all wavelet-based compression algorithms.

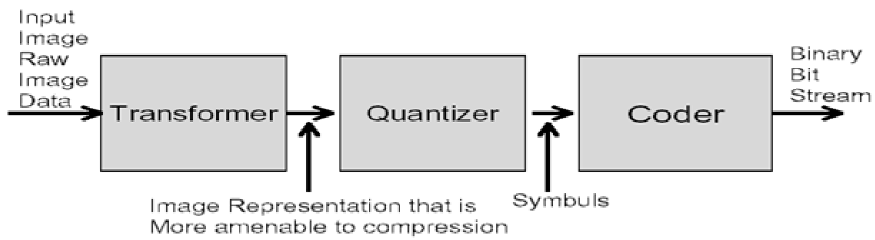


Fig.1:Typical Image Compression System

Types Of Compression Systems: There are two types of compression systems

1.Lossy compression system 2.Lossless compression system

1.Lossy Compression System

Lossy compression techniques can be used in images where some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space.

2. Loss less compression system

Lossless Compression System which aim at minimizing the bit rate of the compressed output without any distortion of the image. The decompressed bit-stream is identical to original bit-stream.

1.1 Introduction to Transformation:

Transform coding constitutes an integral component of contemporary image/video processing applications. Transform coding relies on the premise that pixels in an image exhibit a certain level of correlation with their neighboring pixels. Similarly in a video transmission system, adjacent pixels in consecutive frames show very high correlation. Consequently, these correlations can be exploited to predict the value of a pixel from its respective neighbors. A transformation is, therefore, defined to map this spatial (correlated) data into transformed (uncorrelated) coefficients. Clearly, the transformation should utilize the fact that the information content of an individual pixel is relatively small i.e., to a large extent visual contribution of a pixel can be predicted using its neighbors. A typical image/video transmission system is outlined in Figure 1. The objective of the source encoder is to exploit the redundancies in image data to provide compression. In other words, the source encoder reduces the entropy, which in our case means decrease in the average number of bits required to represent the image. On the contrary, the channel encoder adds redundancy to the output of the source encoder in order to enhance the reliability of the transmission. In the source encoder exploits some redundancy in the image data in order to achieve better compression. The transformation sub-block de correlates the image data thereby reducing *inter pixel redundancy*. The transformation is a lossless operation, therefore, the inverse transformation renders a perfect reconstruction of the original image. The quantize sub-block utilizes the fact that the human eye is unable to perceive some visual information in an image. Such information is deemed redundant and can be discarded without introducing noticeable visual artifacts.

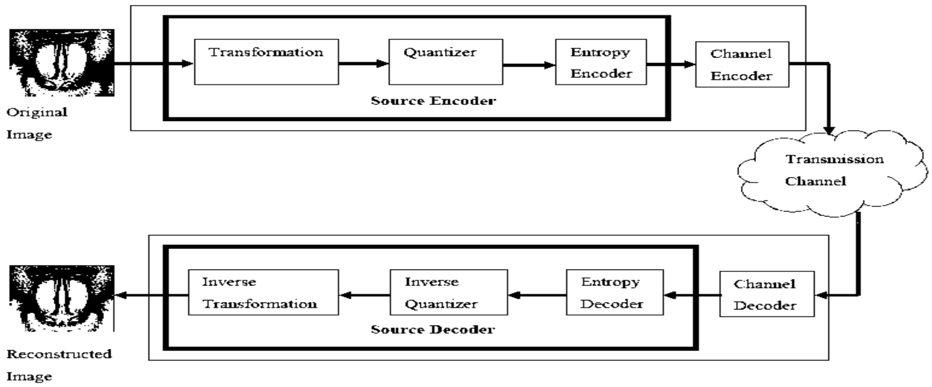


Fig.2 Components of Typical Image/Video Transmission System

Such redundancy is referred to as *psycho visual redundancy*. This idea can be extended to low bit-rate receivers which, due to their stringent bandwidth requirements, might sacrifice visual quality in order to achieve bandwidth efficiency. This concept is the basis for *rate distortion* theory, that is, receivers might tolerate some visual distortion in exchange for bandwidth conservation. The entropy encoder employs its knowledge of the transformation and quantization processes to reduce the output number of bits required to represent each symbol at the quantize. Discrete Cosine Transform (DCT) has emerged as the de-facto image transformation in most visual systems. DCT has been widely deployed by modern video coding standards, for example, MPEG, JVT etc.

2. ERROR METRICS

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) to achieve desirable compression ratios. The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are :

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y) - I'(x,y)\right]^2 \quad \_\_(1)$$

$$PSNR = 20 * \log10\,(255 / \mathrm{sqrt}(MSE)) \quad \_\_(2)$$

where I(x,y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognise that it is a better one.

2.1. Data Compression Transformation:

Data compression ratio, also known as compression power, is used to quantify the reduction in data-representation size produced by data compression . The data compression ratio is analogous to the physical compression ratio it is used to measure physical compression of substances, and is defined in the same way, as the ratio between the uncompressed size and the compressed size . Thus a representation that compresses a 10MB file to 2MB has a compression ratio of 10/2 = 5, often notated as an explicit ratio, 5:1 (read "five to one"), or as an implicit ratio, 5X. Note that this formulation applies equally for compression, where the uncompressed size is that of the original . Sometimes the space savings is given instead, which is defined as the reduction in size relative to the uncompressed size. Thus a representation that compresses 10MB file to 2MB would yield a space savings of 1 - 2/10 = 0.8, often notated as a percentage, 80%. For signals of indefinite size, such as streaming audio and video, the compression ratio is defined in terms of uncompressed and compressed data rates instead of data sizes.

When the uncompressed data rate is known, the compression ratio can be inferred from the compressed data rate.

2.2. Mean Square Error (MSE):

Mean square error is a criterion for an estimator: the choice is the one that minimizes the sum of squared errors due to bias and due to variance. The average of the square of the difference between the desired response and the actual system output. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the "error. The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. In an analogy to standard deviation, taking the square root of MSE yields the root mean squared error or RMSE. Which has the same units as the quantity being estimated. for an unbiased estimator, the RMSE is the square root of the variance, known as the standard error.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}||I(i,j) - K(i,j)||^2 \qquad \text{\_\_\_ (3)}$$

Where m x n is the image size and I(i,j) is the input image and K(i,j) is the retrieved image.

2.3. Peak Signal-to-Noise Ratio(PSNR):

It is the the ratio between the maximum possible power of a signal and the power of corrupting noise .Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered noisy.

The PSNR is defined as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \qquad \text{\_\_\_\_\_\_\_\_(4)}$$

Here, MAXi is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAXI is 2B-1.Typical values for the PSNR in Lossy image and video compression are between 30 and 50 dB, where higher is better. PSNR is computed by measuring the pixel difference between the original image and compressed image. Values for PSNR range between infinity for identical images, to 0 for images that have no commonality. PSNR decreases as the compression ratio increases for an image.

3. Discrete Cosine Transform(DCT):

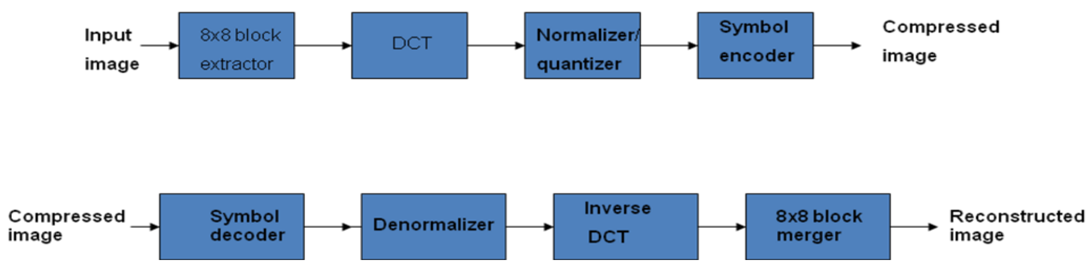


Fig.3 Image Compression using DCT

The discrete cosine transform (DCT) is a technique for converting a signal into elementary frequency components. Like other transforms, the Discrete Cosine Transform (DCT) attempts to de correlate the image data. After de correlation each transform coefficient can be encoded independently without losing compression efficiency.

3.1 Proposed DCT Algorithm:

- The following is a general overview of the JPEG process.
- The image is broken into 8x8 blocks of pixels.
- Working from left to right, top to bottom, the DCT is applied to each block.
- Each block is compressed through quantization.
- The array of compressed blocks that constitute the image is stored in a drastically reduced amount of space.
- When desired, the image is reconstructed through decompression, a process that uses the inverse Discrete Cosine Transform (IDCT).

4. Introduction to Wavelet Transform

The Wavelet Transform (WT) is a way to represent a signal in time-frequency form.Wavelet transform are based on small waves, called wavelets, of varying frequency and limited duration Wavelet Transform uses multiple resolutions where different frequencies are analyzed with different resolutions. This provides a more detailed picture of the signal being analyzed.

A transform can be thought of as a remapping of a signal that provides more information than the original. The Fourier transform fits this definition quite well because the frequency information it provides often leads to new insights about the original signal. However, the inability of the Fourier transform to describe both time and frequency characteristics of the waveform led to a number of different approaches described in the last chapter. None of these approaches was able to completely solve the time–frequency problem. The wavelet transform can be used as yet another way to describe the properties of a waveform that changes over time, but in this case the waveform is divided not into sections of time, but segments of scale. In the Fourier transform, the waveform was compared to a sine function in fact, a whole family of sine functions at harmonically related frequencies. This comparison was carried out by multiplying the waveform with the sinusoidal functions, then averaging (using either integration in the continuous domain, or summation in the discrete domain.

$$X(\omega_m) = \int_{-\infty}^{+\infty} x(t) e^{-j\omega_m t} dt - (5)$$

Almost any family of functions could be used to probe the characteristics of a waveform, but sinusoidal functions are particularly popular because of their unique frequency characteristics: they contain energy at only one specific frequency. Naturally, this feature makes them ideal for probing the frequency makeup of a waveform, i.e., its frequency spectrum. Other probing functions can be used, functions chosen to evaluate some particular behavior or characteristic of the waveform. If the probing function is of finite duration, it would be appropriate to translate, or slide, the function over the waveform, x(t), as is done in convolution and the short-term Fourier transform (STFT).

$$\text{STFT(t,f)}= \int_{-\infty}^{+\infty} x(\tau)(w(t-\tau)e^{-2j\pi f\tau})d\tau - (6)$$

Where f, the frequency, also serves as an indication of family member, and $w(t-\tau)$ is some sliding window function where t acts to translate the window over x. More generally, a translated probing function can be written as:

$$X(t,m) = \int_{-\infty}^{+\infty} x(\tau) f(t-\tau)_m d\tau - (7)$$

Where f(t)m is some family of functions, with m specifying the family number. If the family of functions, f(t)m, is sufficiently large, then it should be able to represent all aspects the waveform x(t). This would then allow x(t) to be reconstructed from X(t,m) making this transform bilateral Often the family of basis functions is so large that X(t,m) forms a redundant set of descriptions, more than sufficient to recover x(t). This redundancy can sometimes be useful, serving to reduce noise or acting as a control, but may be simply unnecessary. Note that while the Fourier transform is not redundant, most transforms would be, since they map a variable of one dimension (t) into a variable of two dimensions (t, m).A multistep analysis-synthesis process can be represented as shown in fig. This process involves two aspects: breaking up a signal to obtain the wavelet coefficients, and reassembling the signal from the coefficients. We've already discussed decomposition and reconstruction at some length. Of course, there is no point breaking up a signal merely to have the satisfaction of immediately reconstructing it. We may modify the wavelet coefficients before performing the reconstruction step. We perform wavelet analysis because the coefficients thus obtained have many known uses, de-noising and compression being foremost among them.But wavelet analysis is still a new and emerging field. No doubt, many uncharted uses of the wavelet coefficients lie in wait. The toolbox can be a means of exploring possible uses and hitherto unknown applications of wavelet analysis. Explore the toolbox functions and see what you discover.

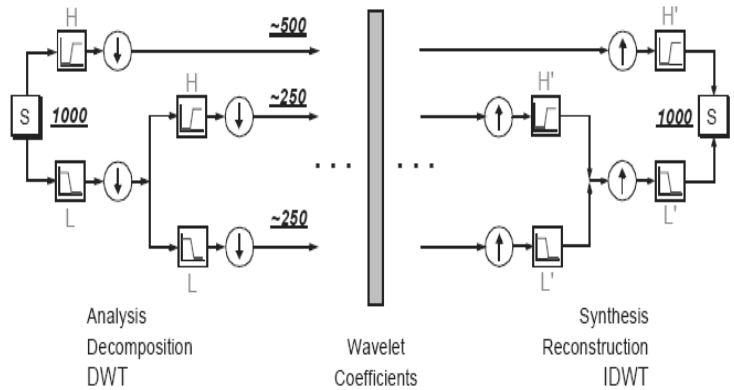


Fig.4: Multistep Decomposition and Reconstruction

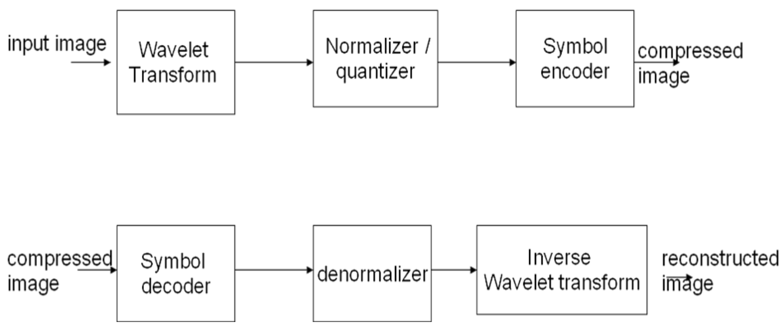


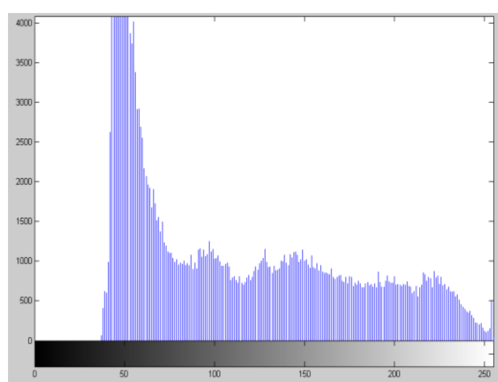
Fig.5:Image Compression Using Wavelets

5. Results

IMAGE1:

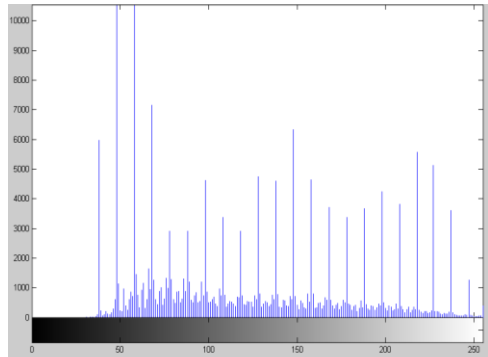
ORIGINAL IMAGE :

ORIGINAL IMAGE HISTOGRAM :



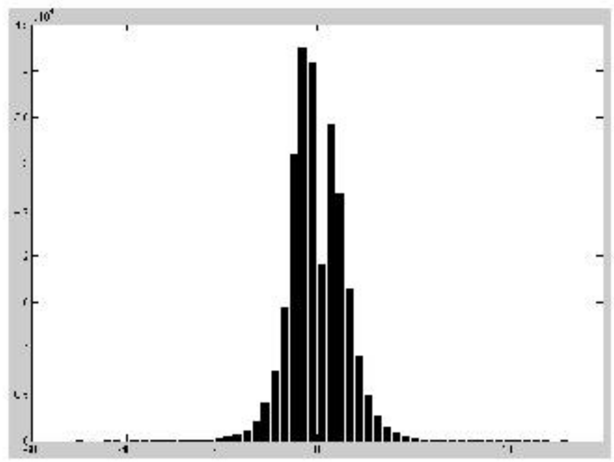
DCT DECOMPRESSED IMAGE:

DECOMPRESSED IMAGE HISTOGRAM:



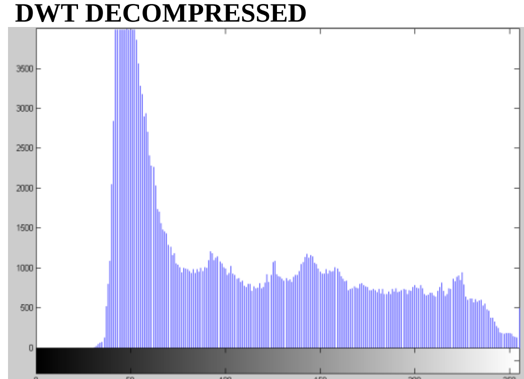
ERROR IMAGE:

ERROR IMAGE HISTOGRAM:



DWT DECOMPRESSED IMAGE:

DWT DECOMPRESSED



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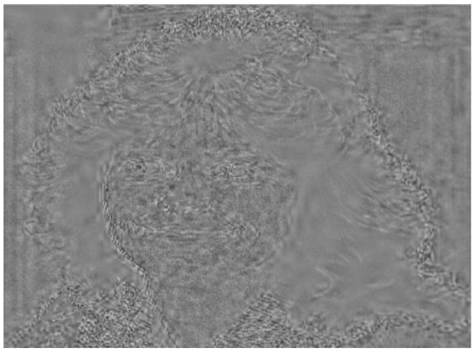

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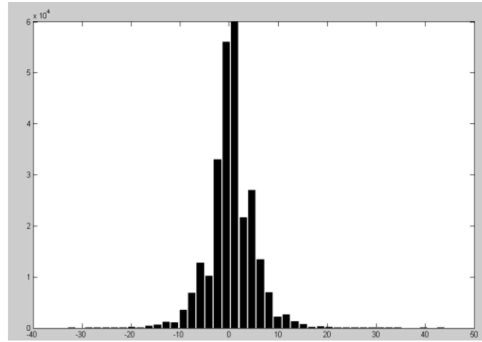
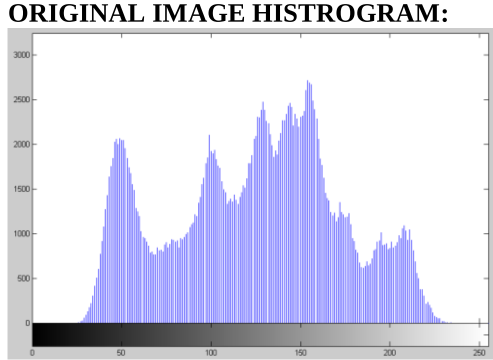


IMAGE 2:

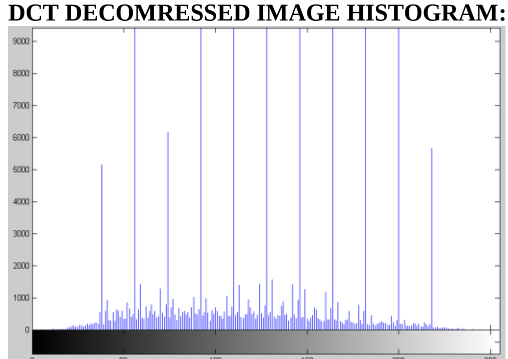
ORIGINAL IMAGE:

ORIGINAL IMAGE HISTROGRAM:



DCT DECOMRESSED IMAGE:

DCT DECOMRESSED IMAGE HISTOGRAM:



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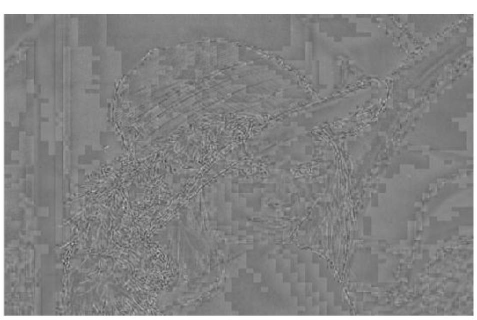

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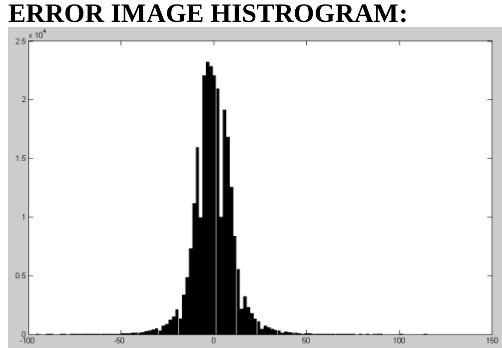

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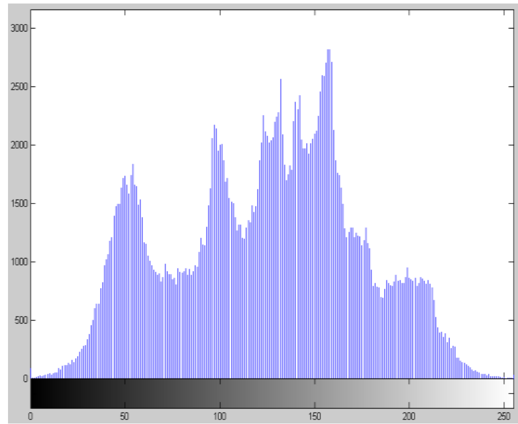
DWT DECOMPRESSED



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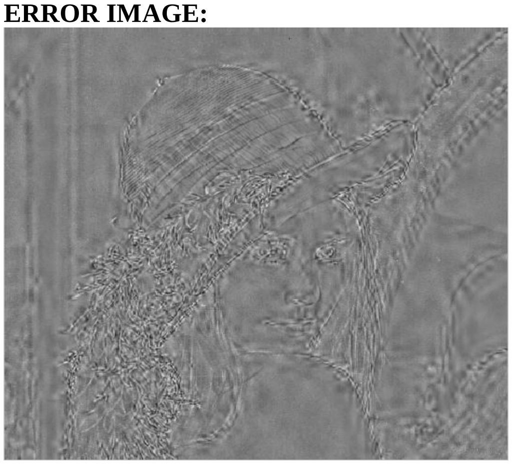

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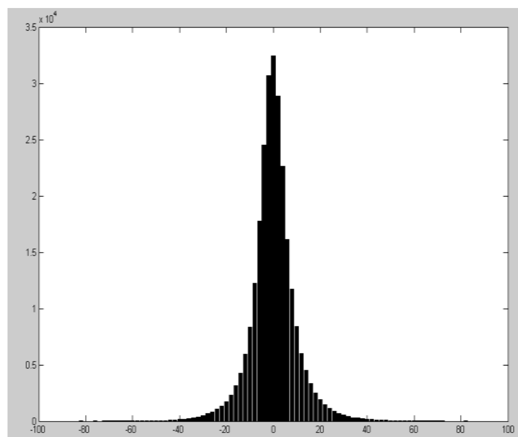
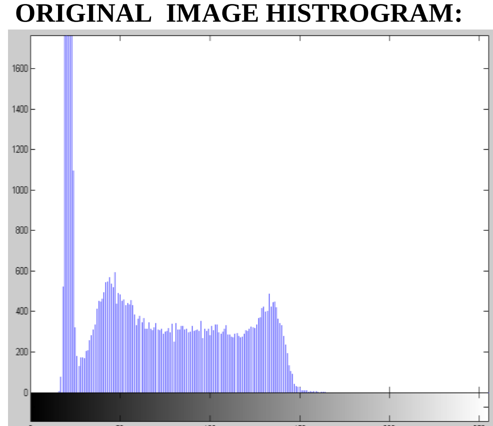


IMAGE 3:

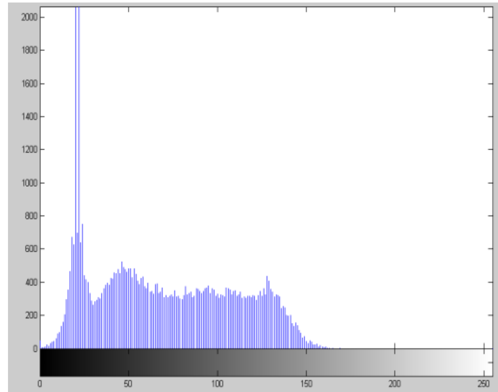
ORIGINAL IMAGE:

ORIGINAL IMAGE HISTROGRAM:



DCT DECOMPRESSED IMAGE:

DCT DECOMPRESSED IMAGE HISTOGRAM:



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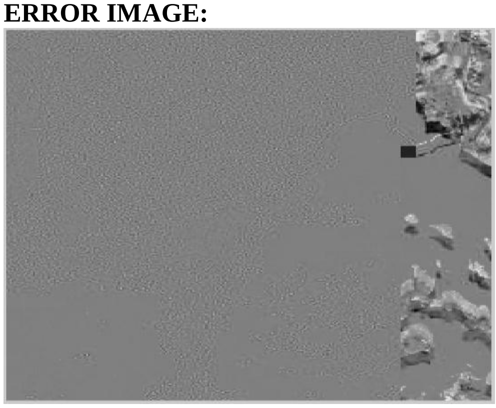

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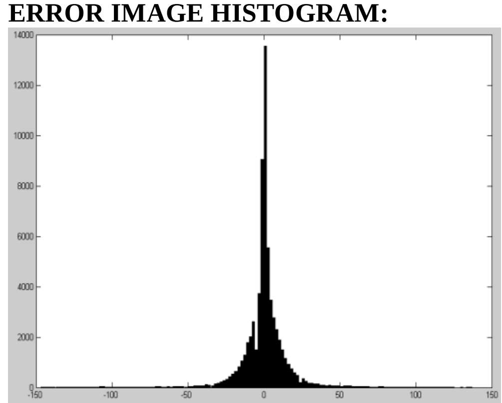

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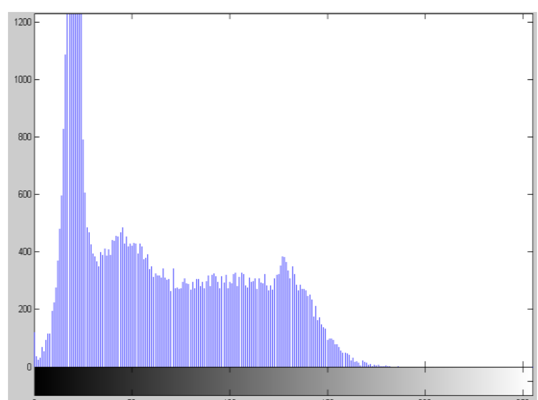

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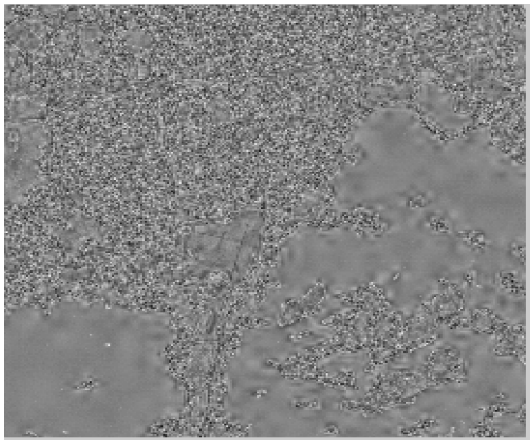

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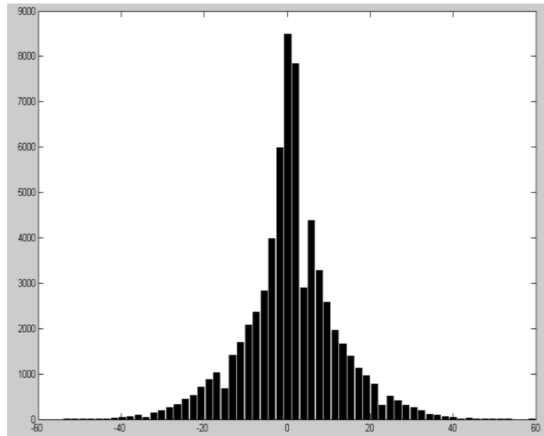
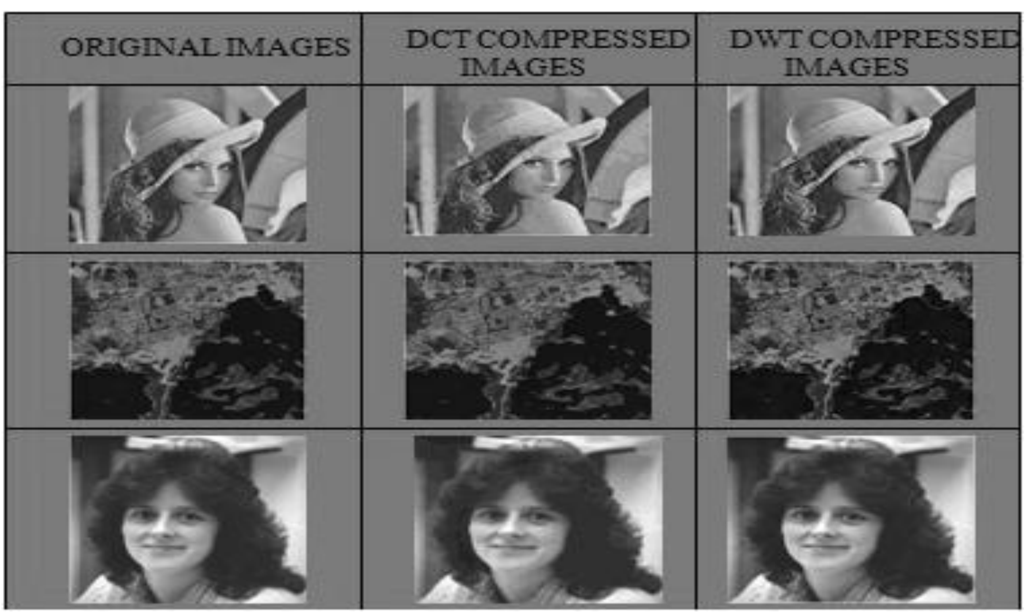


TABLE.1: Performance Comparison of DCT and DWT

	COMPRESSION USED	CR	MSE	PSNR
IMAGE1	DCT	51:1	108	27.78
	DWT	51:1	93.8	28.40
IMAGE2	DCT	6:1	264.4	23.90
	DWT	6:1	126.8	27.09
IMAGE3	DCT	45:1	29.7	33.39
	DWT	45:1	20.15	35.06



6. Conclusion

In this paper, we have considered that DCT and DWT for image compression and decompression. By considering several images as inputs, it is observed that MSE is low and PSNR is high in DWT than DCT based compression. From the results it is concluded that overall performance of DWT is better than DCT on the basis of compression rates. In DISCRETE COSINE TRANSFORM image need to be “blocked”, correlation across the block boundaries is not eliminated. This results in noticeable and annoying ‘blocking artifacts’ particularly at low bit rates.Wavelets are good to represent the point singularities and it cannot represent line singularities. This Paper can further be extended for line singularities with new transform named Ridgelet Transform.

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