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Optimization of Image Compression algorithms using DWT- DCT method

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Abstract: ***Information is generated at very high speed in today's Digital Era. Images have vast share in Information generated, so it's important to reduce the image file size for storage and effective communication. Image compression technique helps in reducing storage and bandwidth requirement for transmission. Optimization of Image compression algorithms is the basic crux of this paper. DCT is most popularly used lossy image compression technique. It has disadvantage that at higher compression ratio the quality of image is lost. DCT is applied to set of images, followed by DWT. The resultant compression metrics are calculated and visual quality of image is analyzed. Experimental analysis shows reduction in storage space requirement and effective optimization using different methodology.***

***Keywords:** Image Compression, Entropy, Block Truncation Coding, Discrete Cosine Transform(DCT) Discrete wavelet tranform(DWT, Image Quality Metrics*

1. Introduction

The rising demand for Multimedia technology and availability of GUI based software had made digital image data inherent part of our life. The amount of data generated by everyday by single user or business user is exponential in nature. Now a day's most of the information is in the form of Images. Images require large amount of space for storage and consumes more bandwidth during transmission. Image Compression plays a vital role in reducing the storage space requirement and helps to increase transmission ratio over network. A gray scale image that is 256 x 256 will have 65, 536 pixels to store and a typical 640 x 480 color image have nearly a million. Downloading of these files from internet can be very time consuming task. Image data comprise of a significant portion of the multimedia data and occupy the major portion of the communication bandwidth for multimedia transmission.

Therefore for the development of efficient techniques image compression has become quite necessary. The image compression technique most often used is transform coding. Transform coding is an image compression technique that first switches to the frequency domain, then does its compression. The transform coefficients should be decor related, to reduce redundancy and to have a maximum amount of information stored in the smallest space [1] [2].

Two fundamental components of compression are redundancy and irrelevancy.

- Redundancies reduction aims at removing duplicate information from the signal source (image/video).
- Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver

In digital image compression, three basic data redundancies can be identified and exploited:
1. Coding redundancy
2. Inter pixel redundancy
3. Psycho visual redundancy

Data compression is achieved when one or more of these redundancies are reduced or eliminated.

Coding redundancy use shorter code words for the more common gray levels and longer code words for the less common gray levels. This is called Variable Length Coding. To reduce this redundancy from an image we go for the Huffman technique were we are assigning fewer bits to the more probable gray levels than to the less probable ones achieves data compression.

Inter pixel redundancy is directly related to the inter pixel correlations within an image. Because the value of any given pixel can be reasonable predicted from the value of its neighbors, the information carried by individual pixels is relatively small. Much of the visual contribution of a single pixel to an image is redundant; it could have been guessed on the basis of its neighbor's values

Psycho visual redundancy: Human perception of the information in an image normally does not involve quantitative analysis of every pixel or luminance value in the image. In general, an observer searches for distinguishing features such as edges or textural regions and mentally combines them into recognizable groupings. The brain then correlates these groupings with prior knowledge in order to complete the image interpretation process. Thus eye does not respond with equal sensitivity to all visual information. Certain information simply has less relative importance than other information in normal visual processing. This information is said to be psycho visually redundant. To reduce psycho visual redundancy we use quantizer. The elimination of psycho visually redundant data results in a loss of quantitative information.

The Organization of this paper is as follows. The Performance Measure are described in Section II, DCT and DWT in section

III, proposed algorithm in section IV, experimental result in section V, and conclusion in Section VI

2. Performance Measure

Image Quality measure plays important role in various image processing applications. Once an image compression technique is designed and implemented its performance evaluation has to be done. The performance metrics needs to be considered in such a way to be able to compare results against other image compression technique. The metrics for image quality can be broadly classified as Subjective and objective. Subjective Quality metrics is used to determine the quality of image by evaluation of images and viewers read images. In case of objective quality metrics some statistical indices are calculated to indicate image quality. After reviewing the literature it can be concluded that certain set of parameter are involved in research to be performed. Some of the parameter can be standard parameter while some of them may be applicable to few selected Compression algorithms.

i) **Compression Ratio (CR)**: The performance of image compression can be specified in terms of compression efficiency which is measured by the compression ratio or by the bit rate. Compression ratio is the ratio of the size to original image to the size of compressed image and bit rate.

$$\mathbf{CR} = \frac{\textbf{Size of Original image}}{\textbf{Size of Compressed Image}}$$

ii) **Peak Signal to Noise Ratio**: It is commonly used as a measure of quality of reconstruction of lossy compression. It is attractive measure for loss of image quality due to simplicity and mathematical convenience. PSNR is qualitative measure based on mean square error (MSE) of the reconstructed image. MSE gives the difference between original image and the reconstructed image and is calculated as follows:

$$\text{MSE}=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[y(i,j)-x(i,j)\right]^2$$

The PSNR is the quality of the reconstructed image and calculated as the inverse of MSE. If the reconstructed image is close to the original image, MSE is small and PSNR take large value. PSNR is dimensionless and expressed in decibel calculated as follows:

$$\text{PSNR}=10\log\left[\frac{L^2}{\text{MSE}}\right]$$

iii) **Structural Similarity Index:** It is method for measuring similarity between two images. It is full reference metrics which mean the measuring of image quality is based on initial uncompressed or distortion free image as reference. SSIM is designed to overcome the inconsistent human eye perception in the traditional method like PSNR. It is defined as the function of three components luminance, contrast and structure and each of this components is calculated separately using (5),(6) & (7) respectively. Luminance change

$$l(x,y)=\frac{2\mu_x\mu_y+c_1}{\mu_x^2+\mu_y^2+c_1}$$

Contrast change,

$$c(x,y)=\frac{2\sigma_x\sigma_y+c_2}{\sigma_x^2+\sigma_y^2+c_2}$$

Structural Change,

$$s(x,y)=\frac{\sigma_{xy}+c_3}{\sigma_x\,\sigma_y+c_3}$$

$$\text{SSIM}(x,y)=l(x,y).c(x,y).s(x,y)$$

where x represent the original image y represent the reconstructed image and

$$\mu_x = average\ of\ x \qquad \mu_y = average\ of\ y$$

$$\sigma_x = variance\ of\ x \qquad \sigma_y = variance\ of\ y$$

$$\sigma_{xy} = covariance\ of\ x\ and\ y$$

c_1 *and* c_2 *are two variables two variables to stabilize the division with weak denominator.*

$$c_1 = (k_1L)^2, c_2 = (k_2L)^2 \quad c_3 = \frac{c_2}{2} \quad k_1 = 0.001$$

$k_2 = 0.002$ *by default L is dynamic range of pixel value*

The resultant SSIM Index is a decimal value between -1 and 1and in case of two identical sets of data value of SSIM is 1.

iv) **Entropy:** It is an important factor to estimate whether the digital image is basically same with the original image. Entropy can be calculated by standard function available in MatLab. E = entropy (I) returns E, a scalar value representing the entropy of gray scale image. Entropy is statistical measure of randomness that can be used to characterize the texture of the input image. It is defined as

$$E = -sum\ (p * \log_2(p))$$

Where p contains the histogram counts returned from imhist.

v) **Edge Measurement (Edge):** This type of quality measure can be obtained from

$$\boldsymbol{Edge} = \frac{\mathbf{1}}{\boldsymbol{MN}}\sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left(\boldsymbol{Q}(\boldsymbol{i},\boldsymbol{j}) - \hat{\boldsymbol{Q}}(\boldsymbol{i},\boldsymbol{j})\right)\right]^{2}$$

Where $Q(i,j)$ and $\acute{Q}(i,j)$ are edge gradients of the original and compressed image using a Sobel operator. The higher the Edge Measurement means the lower of image quality. We need to check for edge measurement parameter since it is observed that in case of BTC there is distortion at the edges.

vi) **Correlation Measurement (C):** The similarity between two digital images could be quantified by correlation function. Each image is Normalized by its root power, So the correlation measurement is defined as

$$C = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} f(m,n)\bar{f}\,(m,n)}{\sqrt{\sum_{m=1}^{M}\sum_{n=1}^{N} f^2(m,n)\sum_{m=1}^{M}\sum_{n=1}^{N}\bar{f}^2(m\,,n)}}$$

$$= \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} x(m,n)\bar{x}\,(m,n)}{\sqrt{\sum_{m=1}^{M}\sum_{n=1}^{N} x^2(m,n)\sum_{m=1}^{M}\sum_{n=1}^{N}\bar{x}^2(m\,,n)}}$$

The higher the value of correlation measurement implies more similarity between the original image and compressed image. In this case we consider the actual image and reconstructed image. The formula is used to calculate correlation mathematically and is built in function available in MATLAB.

3. DCT and DWT

The discrete cosine transform (DCT) represents an image as a sum of sinusoids of varying magnitudes and frequencies. The DCT has the property that, for a typical image, most of the visually significant information is concentrated in just a few coefficients of the DCT. The DCT works by separating images into the parts of different frequencies. During a step called

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Quantization, where parts of compression actually occur, the less important frequencies are discarded. Then the most important frequencies that remain are used to retrieve the image in decomposition process. As a result, reconstructed image is distorted [3].

All mainstream encoders use the Discrete Cosine Transform (DCT) to perform transform coding that maps a time domain signals to a frequency domain representation. The frequency domain spectrum can be compressed by truncating low intensity regions. However, the DCT has drawbacks like computation takes long time and grows exponentially with signal size. If we want to calculate the DCT of entire video frame it will require unacceptable amount of time. The Solution is to partition video into small blocks and applies DCT to each partition which may lead to degradation of picture quality. The Discrete Wavelet Transform offers a better solution. DWT is another transform that maps time domain signals to frequency domain representations. The DWT can be computed by performing a set of digital filters which can be done quickly. This allows us to apply the DWT on entire signals without taking a significant performance hit. By analyzing the entire signal the DWT captures more information than the DCT and can produce better results. The DWT separates the image's high frequency components from the rest of the image, resizes the remaining parts and rearranges them to form a new 'transformed' image [3].

4. Proposed Algorithm

In this paper we proposed two different algorithms and try to optimize the methodology so as to maximize Compression ratio.

Method 1 (DCT Low pass)

Step 1: Load the image to be compressed.

Step 2: Decompress the image planes using DCT and Specific Block Size.

Step 3: Reconstruct the image using iDCT

Step 4: Apply Low Pass Filtering to smoothen the edges.

Step 5: Save the compressed image and calculate Compression

Method 2 (DWT DCT Method)

Step 1: Load the image to be compressed.

Step 2: Split the original image to Y, C_b and Cr color planes.

Step 3: Decompress the image planes using DWT.

Step 4: Apply Subband coding and shift data to create zero matrix.

Step 5: Create the transform array using DCT and Eliminate the zero matrixes using block N x N.

Step6: Reconstruct the image using iDCT

Step 7: Save the compressed image and calculate Compression

The next section discusses the result and outcome based on performance parameter. The overall result reflects better result compared to previous methodology used for experimentation.

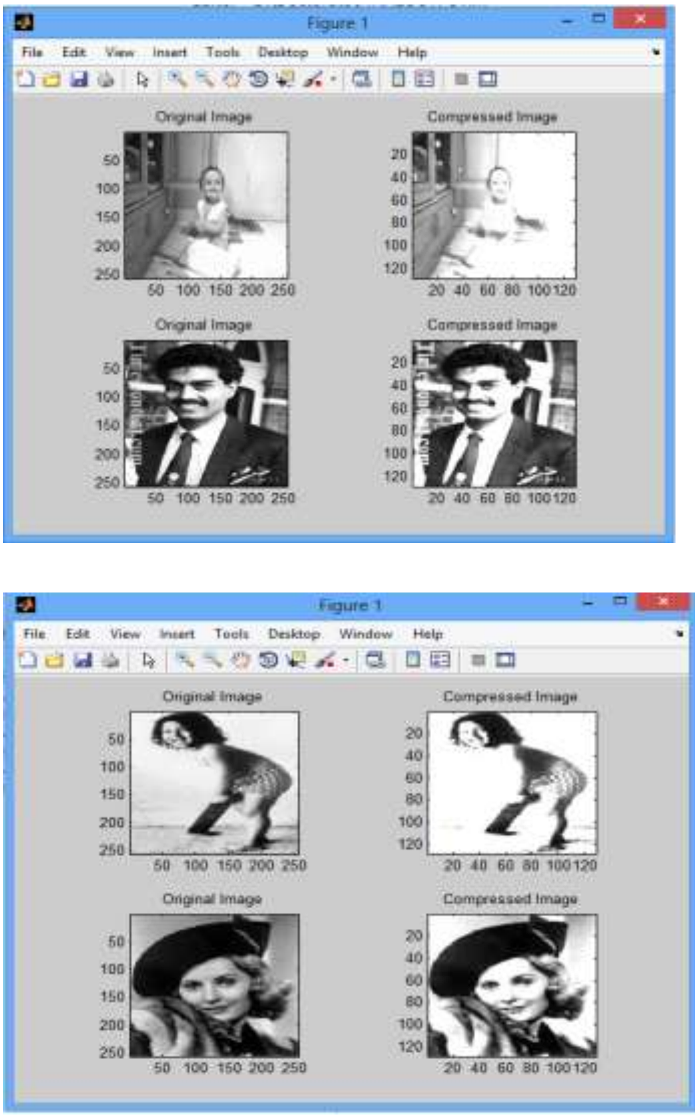

Figure1. Result of DCT DWT

5. Experimental Results

The performance of both the method was evaluated and tabulated as shown in Table 1 and Table 2. Table 1 highlights the DCT method and DCT with low pass filter applied to compressed image along with performance parameters. Some set of standard images along with other format are considered. Table 2 highlights the DWT DCT methodology applied to the set of test images. Table 3 highlights the Correlation and Entropy for the set of images used. Table 4 highlights the result when DCT DWT is used for optimization of compression ratio. The Discussion regarding each table follows in this section

Image	Original	DWT	DCT	Correlation
Test1.jpg	**7.128**	**6.2112**	**3.4781**	**0.9966**
Test2.jpg	**7.6405**	**5.7263**	**3.7794**	**0.9932**
Test5.jpg	**7.4287**	**4.6333**	**3.4684**	**0.9959**
Test9.jpg	**7.431**	**7.6511**	**3.4417**	**0.9935**
Test11.jpg	**6.7616**	**6.8725**	**3.8558**	**0.9726**
Test15.jpg	**7.6317**	**6.6027**	**3.8717**	**0.9919**
Test18.jpg	**7.4908**	**5.3608**	**3.9029**	**0.9854**
Test20.jpg	**4.1354**	**3.5140**	**3.8557**	**0.9908**
Test24.jpg	**7.4884**	**5.1169**	**3.7457**	**0.9719**
Test30.jpg	**6.1985**	**6.1706**	**3.6054**	**0.9909**

Table 3 Entropy and Correlation for DWTDCT

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Image	BLOCK SIZE = 8		BLOCK SIZE = 16		BLOCK SIZE = 32	
	DCT	MODDCT	DCT	MODDCT	DCT	MODDCT
Lena	 **MSE=3.109** **RME=176.121** **SNR=14.301** **PSNR =7.4801** **CR=1.030** **En=7.445**	 **MSE=1.742** **RME=132.016** **SNR=88.823** **PSNR =13.245** **CR=1.032** **En=7.276**	 **MSE=3.322** **RME=182.283** **SNR=31.202** **PSNR =6.792** **CR=1.023** **En=7.445**	 **MSE=1.742** **RME=132.011** **SNR=88.506** **PSNR =13.245** **CR=1.023** **En = 7.276**	 **MSE=3.432** **RME=185.265** **SNR=66.434** **PSNR =6.4676** **CR=1.021** **En= 7.445**	 **MSE=1.742** **RME=132.007** **SNR=88.443** **PSNR =13.245** **CR=1.021** **En=7.276**
Barbara	 **MSE=3.732** **RME=193.184** **SNR=14.602** **PSNR =5.630** **CR=1.073** **En = 7.343**	 **MSE=2.090** **RME=144.579** **SNR=110.910** **PSNR =11.427** **CR=1.029** **En = 7.106**	 **MSE=3.989** **RME=199.745** **SNR=31.491** **PSNR =4.962** **CR=1.056** **En = 7.343**	 **MSE=2.090** **RME=144.597** **SNR=111.682** **PSNR =11.424** **CR=1.091** **En = 7.106**	 **MSE=4.123** **RME=203.034** **SNR=68.191** **PSNR =4.636** **CR=1.053** **En = 7.343**	 **MSE=2.090** **RME=144.578** **SNR=112.45** **PSNR =11.4271** **CR=1.021** **En = 7.106**

Table 1 Comparative Result of DCT and DCT with Low Pass Filter

Image Name	**Original Image**	**Compressed Image**	**Parameters**
Cameraman			**Original Size=65KB** **Compressed Size=17KB** **MSE=177.07** **RME=133.305** **SNR=167.315** **PSNR =13.050** **Compression =75%**
Test7.jpg			**Original Size=13.3 KB** **Compressed Size=4.95 KB** **MSE=164.22** **RME=128.149** **SNR=168.388** **PSNR =13.839**
Test5.jpg			**Original Size=8.42 KB** **Compressed Size=2.46 KB** **MSE=326.26** **RME=180.626** **SNR=165.017** **PSNR =6.974** **Compression =70.78%**
Test8.jpg			**Original Size=8.13 KB** **Compressed Size=2.80 KB** **MSE=383.68** **RME=195.877** **SNR=165.158** **PSNR =5.353** **Compression =65.55%**
Test11.jpg			**Original Size=10 KB** **Compressed Size=3.87KB** **MSE=177.07** **RME=133.305** **SNR=167.315** **PSNR =13.050** **Compression =75%**

Table 2 Result of DWT DCT Method with performance parameter

Table 1 shows the result for Method 1 and parameters calculated for same. The various block size consider are represented in the table. Initially DCT is applied to original image and result reflects blurring effect or step at edges. To remove this effect low pass filtering is applied. It is observed that the quality of image has improved. Moreover in DCT methodology it is known that it follows zig- zag pattern for reduction. The image pixels are reduced to half while the process is being applied. Compression ratio indicates that image is compressed to substantial ratio and quality is also maintained. This helps in reducing storage space.

Table 2 shows the result of method 2. We apply DWT to original image of size 256 x 256, so it has 65536 pixel values. After applying the DWT we consider LL region of DWT which is 128 x 128 hence it has 16384 pixel values. DCT is applied to this and image is reconstructed. It is found that it reduces the storage space for images by more than 50% and helps in reducing the transmission bandwidth requirement.

Table 3 indicates Entropy and correlation parameter. Correlation indicates the matching between original image and reconstructed image i.e. compressed image. In most of the images that are tested for optimization it is observed that

Image	**Original**	**DCT**	**DWT**
Test1.jpg	**7.128**	**2.6095**	**0.7150**
Test2.jpg	**7.6405**	**2.5165**	**0.6514**
Test7.jpg	**7.6032**	**1.7743**	**0.7243**
Test30.jpg	**6.1985**	**3.2237**	**0.9479**

Table 4 Entropy and Correlation for DCTDWT

more than 99% image is reconstructed after applying compression technique. The table indicates values for correlation for various test images in last column. Entropy is obtained in three stages for given set of test image. Original, DWT DCT. When we calculate Entropy the compressed value at each level should not exceed the value obtained for the original image. For all images this pattern prevails thus justify that optimization is obtained. Table 4 indicate the Entropy value for DCT DWT Method

6. Conclusion

In this paper two different methods are suggested for optimization of image compression algorithm. It can be concluded that result obtain indicate reduction in storage space requirement. This will directly help in reducing the transmission bandwidth requirement for various images. The second method provide better result compared to the first one. Moreover it is observed that time required to perform compression is reduce compared to traditional approach. In future these methods can be enhanced further by applying some other standard algorithm in mixed mode.

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