

# RGB Image Compression Using Two Dimensional Discrete Cosine Transform

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**Abstract**--To addresses the problem of reducing the memory space and amount of data required to represent a digital image. Image compression plays a crucial role in many important and adverse applications and including televideo conferencing, remote sensing, document, medical and facsimile transmission. The need for an efficient technique for compression of Images ever increasing because the raw images need large amounts of disk space seems to be a big disadvantage during transmission & storage. Even though there are so many compression technique already available- a better technique which is faster, memory efficient and simple surely suits the requirements of the user. In this paper the Spatial Redundancy method of image compression using a simple transform technique called Discrete Cosine Transform is proposed. This technique is simple in implementation and utilizes less memory. A software algorithm has been developed and implemented to compress the given RGB image using Discrete Cosine Transform techniques in a MATLAB platform. In this paper rgb image is compressed upto 70%, 60%, 40% and 20% and optimum results are obtained. The analysis of results obtain has been carried out with the help of MSE (mean square error) and PSNR (peak signal to noise ratio).

**Keywords**--Image compression, DCT, IDCT, DCT2, IDCT2, MSE, PSNR, Redundancy.

## I. INTRODUCTION

The digital image processing refers to processing digital images by means of a digital computer. The digital image processing have authentic applications in various fields. In digital image processing we processed the images. In simple words we can say that this field of digital image processing encompasses processes whose input and outputs are images. By sampling and quantizing a continuous tone picture we get a digital image, which requires enormous memory for storage. We can understand it by following example. For instance, a 24 bit colour image with 512x512 pixels will occupy 768 Kbyte storage on a disk, and a picture twice of this size will not fit in a single floppy disk. To transmit such an image over a 28.8 Kbps modem would take almost 4 minutes. Another example are (a). The Encyclopedia Britannica scanned at 300 pixels per inch and 1 bit per pixel requires 25,000 pages x1,000,000 bytes per page = 25 gigabytes. (b). Video is even bulkier: 90 minute movie at 640x480 resolution spatially, 24 bit per pixel, 24 frames per

second, requires  $90 \times 60 \times 24 \times 640 \times 480 \times 3 = 120$  gigabytes [1]. Its applications are in HDTV, film, remote sensing and satellite image transmission, network communication, image storage, medical image processing, fax, image database and in other earth resource application[2].

To store images, and make them available over the network (e.g. the internet), efficient and reliable compression techniques are required. Image compression addresses the problem of reducing the amount of data required to represent a digital image. The underlying basis of the reduction process is the removal of redundant data[1],[2]. According to mathematical point of view, this amounts to transforming a two-dimensional pixel array into a statistically uncorrelated data set. The transformation is applied to the image before transmission or storage of the image. At receiver, the compressed image is decompressed to reconstruct the original image or an approximation to it. The example given above clearly shows the importance of compression.

To reduce (a) the amount of data required for representing sampled digital images (b) reduce the space required to save the data as well as to reduce the cost for storage and transmission. Therefore image compression plays a key role in many important applications as mentioned earlier. The image to be compressed is RGB posses red, green and blue colours. The different techniques for compressing the images available are broadly classified into two classes called lossless and lossy compression techniques. As the name suggests in lossless compression techniques, no information regarding the image is lost. In simple words, the reconstructed image from the compressed image is identical to the input or original image in every sense. Whereas in lossy compression, some image information is lost during compression process, i.e. the reconstructed image from the compressed image is similar to the original image but not identical to it.

Transform coding has become the standard paradigm in image compression. Jiankum Li et al. presented a paper on "Layered DCT still image compression" in which they presented a new thresholding multiresolution block matching algorithm. It reduced the processing time from 14% to 20%, compared to that of fastest existing

multiresolution technique with the same quality of reconstructed image[3]. Zixiang Xiong et al. presented a paper on “A comparative study of DCT and wavelet based image coding”. In which they got different PSNR values, for 0.125(b/p) rate PSNR for SPIHT with 3 level wavelet 30.13dB(Leena) and 24.16dB (Barbara) and with Embedded DCT are 28.50dB (Leena) and 24.07(Barbara). For 1.00 (b/p) rate 40.23dB (Leena), 36.17dB (Barbara) and DCT Embedded 39.60dB (Leena) and 36.08(Barbara)[4]. Panos Nasiopoulos and Rabab K. Ward presented a paper on “A high quality fixed length compression scheme for color images”. In which they performed compression operation with DCT by fixed length code words. They applied fixed length compression method (FLC) and absolute moment block truncation coding (AMBTC). In FLC method they obtained less RMSE in comparison to AMBTC method that is for Leena’s image 4.76dB and 6.88dB RMSE achieved by FLC and AMBTC respectively[5]. DCT is used because of its nice decorrelation and energy compactation properties[6]. In recent years much of the research activities in image coding have been focused on the discrete wavelet transform. While the good results obtained by wavelet coders (e.g. the embedded zerotree wavelet(EZW) coder[7] and the set partitioning in hierarchical trees (SPIHT) coder [8] are partly attributable to the wavelet transform.

The main objective of proposed research is to compress images by two dimensional discrete cosine transform (DCT2) and to decrease the transmission time for transmission of images and then reconstructing the original image by two dimensional inverse discrete cosine transform (IDCT2). The entire paper is organized in the following sequence. In section -2 describe the various types of data redundancies are explained, section-3 existing methods of compressions are explained, In section-4 the Discrete Cosine Transform is discussed. The algorithm developed and the results obtained are discussed in section 5 and 6 followed by conclusion and future work.

## II. PRINCIPLES BEHIND COMPRESSION

A common characteristic of most images is that the neighbouring pixels are correlated and therefore contain redundant bit or information [9]. The next task therefore is to find less correlated bits or representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancies reduction aims at removing duplication from the signal source (image/video), Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS) [10]. There are three types of redundancies namely coding redundancy, interpixel redundancy and psycho visual redundancy which are explained in preceding sections.

### II.I CODING REDUNDANCY

In coding redundancy fewer bits to represent frequently occurring symbols. In other words, if the gray levels of an image are coded in a way that uses more code symbol than absolutely necessary to represent each gray level, the resulting image is said to be code redundancy. If we draw the histogram of an image, we see that

$$P_r(r_k) = n_k / n \quad (2.1)$$
$$k = 0, 1, 2, \dots, L-1$$

Where,  $n_k$  is number of time of  $k$  pixel occurrence,  $n$  is number of total pixel and  $P_r(r_k)$  is probability of occurrence of  $k^{\text{th}}$  pixel. We get a diagram, that will show that a particular gray level has  $P$  probability of occurrence. Generally, the code redundancy is present when the codes assigned to take full advantage of the probabilities of the event [1].

To reduce this redundancy from an image Huffman technique is generally used, assigning fewer bits to the more probable gray levels than to the less probable ones achieves data compression. Such type of process commonly is referred to as variable length coding[1],[2].

### II.II INTER PIXEL REDUNDANCY

In inter pixel redundancy neighbouring pixels have almost same values. Inter pixel redundancy, which 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 neighbours, the information carried by individual pixels is relatively small. A variety of names, including spatial redundancy, geometric redundancy, and interframe redundancies have been coined to refer to these interpixel dependencies. In order to reduce the interpixel redundancies in an image, the 2-D pixel array normally used for human viewing and interpretation must be transformed into a more efficient but usually non-visual format[1],[2]. To reduce the interpixel redundancy we use various techniques such as: (a). Predictive coding (b). Delta compression (c). Run length coding and (e). Constant area coding .

### II.III PSYCHO VISUAL REDUNDANCY

In psycho visual redundancy Human Visual System (HVS) cannot simultaneously distinguish all colours. Human perception of the information in an image normally does not involve quantitative analysis of every pixel value in the image. In general, an observer searches for distinguishing features of image such as edges or textural regions and mentally combines them into recognizable groupings. Certain information simply has less relative importance than other information in normal visual processing. This type of information is said to be psycho visually redundant. Unlike coding redundancy and interpixel redundancy, psychovisual redundancy is associated with real or quantifiable visual

information[1],[2]. Removal of psychovisual redundancy is possible only because the information itself is not important for normal visual processing. Removal of psychovisual redundant data results in a loss of quantitative information. So it is an irreversible process.

To reduce psycho visual redundancy we generally preferred quantizer. Since there is a loss of quantitative information in quantization process. Quantization results in lossy data compression, so it is a irreversible process.

### III. TYPES OF COMPRESSION

Compression can be divided into two categories, as Lossless and Lossy compression. In lossless compression, the reconstructed image after compression is numerically identical to the original image in every sense [9]. In lossy compression scheme, the reconstructed image contains degradation relative to the original. In simple words we can say that in lossy compression, the reconstructed image after compression is not numerically identical to the original image. Lossy technique causes image quality degradation in each compression or decompression step[11],[12]. In general, lossy techniques provide greater compression ratios as compared to lossless techniques. The following are the some of the lossless and lossy data compression techniques:

#### III.I. LOSSLESS CODING TECHNIQUES

- (a). Entropy coding
- (b). Area coding
- (c). Arithmetic encoding
- (d). Run length encoding
- (e). Huffman encoding

#### III.II. LOSSY CODING TECHNIQUES

- (a) Transform coding (FT/DCT/Wavelets)
- (b) Predictive coding

### IV. THE DISCRETE COSINE TRANSFORM

DCT Definition: The discrete cosine transform (DCT) represents an image as a sum of sinusoids of varying magnitudes and frequencies. The dct2 function computes the two-dimensional discrete cosine transform (DCT) of an image. The DCT has the property that, for a typical image, most of the visually significant information about the image is concentrated in just a few coefficients of the DCT. For this reason, the DCT is often used in image compression applications. For example, the DCT is the heart of the international standard lossy image compression algorithm known as JPEG.

The important feature of the DCT is that it takes correlated input data and concentrates its energy in just the first few transform coefficients. If the input data consists of correlated quantities, then most of the  $n$  transform coefficients produced by the DCT are zeros or small numbers, and only a few are large (normally the

first ones). The early coefficients contain the important (low-frequency) image information and the later coefficients contain the less-important (high-frequency) image information. Compressing data with the DCT is therefore done by quantizing the coefficients. The small ones are quantized coarsely (possibly all the way to zero), and the large ones can be quantized finely to the nearest integer. After quantization, the coefficients (or variable-size codes assigned to the coefficients) are written on the compressed stream. Decompression is done by performing the inverse DCT on the quantized coefficients. This results in data items that are not identical to the original ones but are not much different [2],[13],[14],[15],[16].

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.

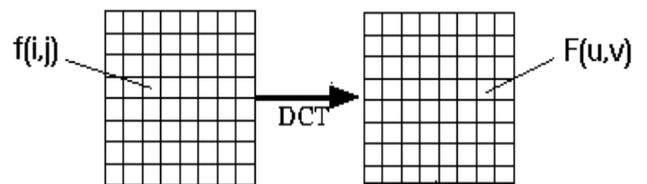


Fig. 1 Discrete Cosine Transform

#### DCT Encoding

The general equation for a 1D ( $N$  data items) DCT is defined by the following equation:

$$F(u) = (2/N)^{1/2} \sum_{i=0}^{N-1} \Lambda(i) \cdot \cos[(\pi \cdot u / 2 \cdot N)(2i + 1)] f(i)$$

$$F(u) = (2/N)$$

and the corresponding *inverse* 1D DCT transform is simple  $F^{-1}(u)$ , i.e.:

where

$$\Lambda(i) = \begin{cases} 1/\sqrt{2} & \text{for } \xi = 0 \\ 1 & \text{otherwise} \end{cases}$$

The general equation for a 2D ( $N$  by  $M$  image) DCT is defined by the following equation:

$$F(u, v) = (2/N)^{1/2} (2/M)^{1/2} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \Lambda(i) \cdot \Lambda(j) \cdot \cos[(\pi \cdot u / 2 \cdot N)(2i + 1)] \cos[(\pi \cdot v / 2 \cdot M)(2j + 1)] f(i, j)$$

and the corresponding *inverse* 2D DCT transform is simple  $F^{-1}(u, v)$ , i.e.:

where

$$\Lambda(\xi) = \begin{cases} 1/\sqrt{2} & \text{for } \xi = 0 \\ 1 & \text{otherwise} \end{cases}$$

The basic operation of the DCT is as given below:

- i. The input image is  $N$  by  $M$

- ii.  $f(i,j)$  is the intensity of the pixel in row  $i$  and column  $j$
- iii.  $F(u,v)$  is the DCT coefficient in row  $k_1$  and column  $k_2$  of the DCT matrix.
- iv. For most images, much of the information or signal energy lies at low frequencies and these appear in the upper left corner of the DCT.
- v. Compression is achieved since the lower right values represent higher frequencies, and are often small - small enough to be neglected with little visible distortion.
- vi. The DCT input is an 8 by 8 array of integers and this array contains each pixel's gray scale level
- vii. 8 bit pixels have levels from 0 to 255
- viii. Therefore an 8 point DCT would be:  
where

$$\Lambda(\xi) = \begin{cases} 1/\sqrt{2} & \text{for } \xi = 0 \\ 1 & \text{otherwise} \end{cases}$$

- ix. The output array of DCT coefficients contains integers; these can range from -1024 to 1023.
- x. It is computationally easier to implement and more efficient to regard the DCT as a set of basis functions which given a known input array size (8 x 8) can be precomputed and stored.

This involves simply computing values for a convolution mask (8 x8 window) that get applied (sum values x pixel the window overlap with image apply window across all rows/columns of image).

The values as simply calculated from the DCT formula. The 64 (8 x 8) DCT basis functions are illustrated in given below figure.

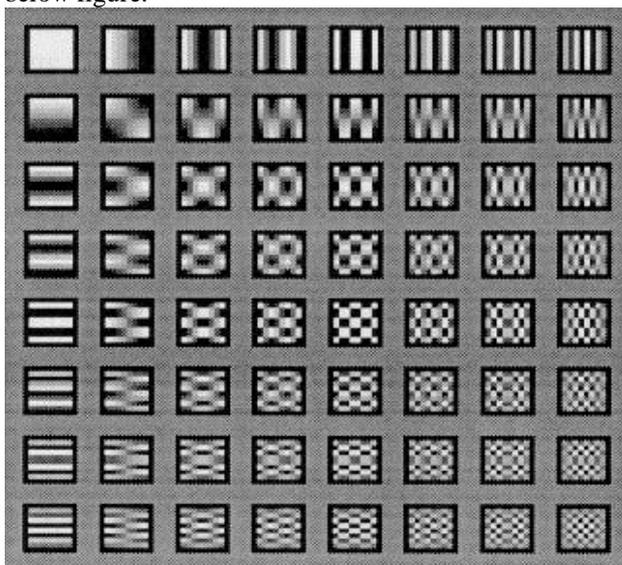
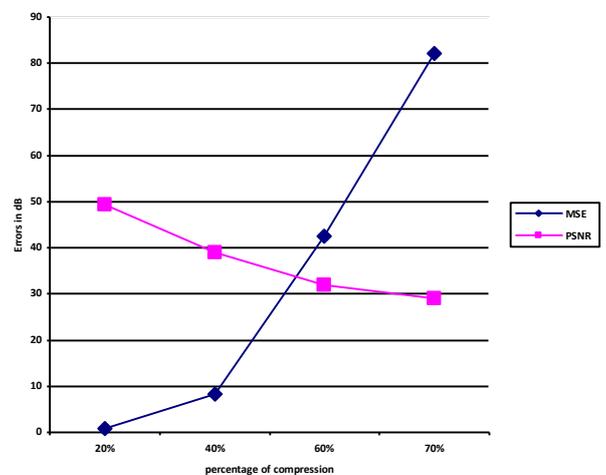


Fig. 2 DCT basis functions

## V. DEVELOPMENT OF IMAGE COMPRESSION ALGORITHM

- Step 1- Read the image on to the workspace of the MATLAB.
- Step 2- Resize the input image (100x100)
- Step 3- Now run the loop for 70% compression
- Step 4- Take DCT2 of 'r' (red component)
- Step 5- Take DCT2 of 'g' (green component)
- Step 6- Take DCT2 of 'b' (blue component)
- Step 7- Take IDCT2 of 'r' (red component)
- Step 8- Take IDCT2 of 'g' (green component)
- Step 9- Take IDCT2 of 'b' (blue component)
- Step 10- Now run the loop for 60 % compression
- Step 11- Take DCT2 of 'r' (red component)
- Step 12- Take DCT2 of 'g' (green component)
- Step 13- Take DCT2 of 'b' (blue component)
- Step 14- Take IDCT2 of 'r' (red component)
- Step 15- Take IDCT2 of 'g' (green component)
- Step 16- Take IDCT2 of 'b' (blue component)
- Step 17- Now run the loop for 40% compression
- Step 18- Take DCT2 of 'r' (red component)
- Step 19- Take DCT2 of 'g' (green component)
- Step 20- Take DCT2 of 'b' (blue component)
- Step 21- Take IDCT2 of 'r' (red component)
- Step 22- Take IDCT2 of 'g' (green component)
- Step 23- Take IDCT2 of 'b' (blue component)
- Step 24- Now run the loop for 20% compression
- Step 25- Take DCT2 of 'r' (red component)
- Step 26- Take DCT2 of 'g' (green component)
- Step 27- Take DCT2 of 'b' (blue component)
- Step 28- Take IDCT2 of 'r' (red component)
- Step 29- Take IDCT2 of 'g' (green component)
- Step 30- Take IDCT2 of 'b' (blue component)
- Step 31- Then we performed image compression
- Step 32- After compression we obtained the MSE and PSNR values in dB.

## VI. RESULTS



RGB COPMRESSED IMAGE



MSE and PSNR Table

Compression's percentage	MSE (in dB)	PSNR (in dB)
20%	0.7582	49.3669
40%	8.3713	38.9369
60%	42.4486	31.8862
70%	82.0815	29.0223

Conclusion

In this paper we compressed the images by our choice (70%, 60%, 40% & 20%) using 2dimensional discrete cosine transform. Original input image is compared with reconstructed image with respect to MSE and PSNR. This compression algorithm provide a better quality picture as we are increasing percentage of compression. The above algorithm can be used to compress the image that is used in the web applications and where we need different percentage of compression as it need less processing time. Furthermore in future we can analyse different image transform algorithms for improvement of different parameters.

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