Review: Image Compression Algorithm

Maneesha Gupta
Research Scholar,Electronics and communicationEngineering
Maharishi Markandeshwar University,Mullana(Ambala)
maneesha28.gupta@gmail.com

Dr.Amit Kumar garg
Professor & Head Of Department,Electronics and Communication Engineering
Maharishi Markandeshwar University,Mullana(Ambala)
agarg001@yahoo.com

Mr.Abhishek Kaushik
Assistant Professor
Shri Krishan Institute Of Engineering and Technology,Kurukshetra
abhikaushik2803@gmail.com

***Abstract*-Image compression is the application of Data compression on digital images. The discrete cosine transform (DCT) is a technique for converting a signal into elementary frequency components. It is widely used in image compression. Here we develop some simple functions to compute the DCT and to compress images. An image compression algorithm was comprehended using Matlab code, and modified to perform better when implemented in hardware description language. The IMAP block and IMAQ block of MATLAB was used to analyse and study the results of Image Compression using DCT and varying co-efficients for compression were developed to show the resulting image and error image from the original images. Image Compression is studied using 2-D discrete Cosine Transform. The original image is transformed in 8-by-8 blocks and then inverse transformed in 8-by-8 blocks to create the reconstructed image. The inverse DCT would be performed using the subset of DCT coefficients. The error image (the difference between the original and reconstructed image) would be displayed. Error value for every image would be calculated over various values of DCT co-efficients as selected by the user and would be displayed in the end to detect the accuracy and compression in the resulting image.**

***Keywords*: Discrete Cosine Transform, Pixels, Inverse Fourier, Encoding, Decoding, Quantization, Entropy.**

1. Introduction

Data compression is the technique to reduce the redundancies in data representation in order to decrease data storage requirements and hence communication costs. Reducing the storage requirement is equivalent to increasing the capacity of the storage medium and hence communication bandwidth. Thus the development of efficient compression techniques will continue to be a design challenge for future communication systems and advanced multimedia applications.Data is represented as a combination of information and redundancy. Information is the portion of data that must be preserved permanently in its original form in order to correctly interpret the meaning or purpose of the data. Redundancy is that portion of data that can be removed when it is not needed or can be reinserted to interpret the data when needed. Most often, the redundancy is reinserted in order to generate the original data in its original form. A technique to reduce the redundancy of data is defined as Data compression. The redundancy in data representation is reduced such a way that it can be subsequently reinserted to recover the original data, which is called decompression of the data.

Data compression can be defined as a method that takes an input data D and generates a shorter representation of the data c(D) with less number of bits as compared to that of D. The reverse process is called decompression, which takes the compressed data c(D) and generates or reconstructs the data D‟ as shown in Figure 1. Sometimes the compression (coding) and decompression (decoding) systems together are called a "CODEC"

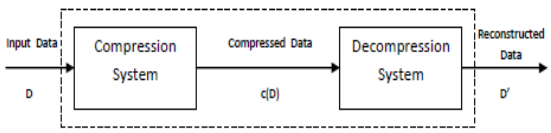
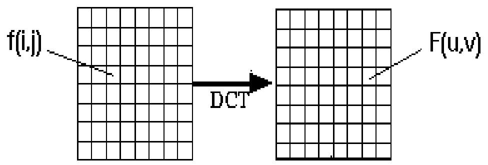


Figure 1: CODEC

The reconstructed data D‟ could be identical to the original data D or it could be an approximation of the original data D, depending on the reconstruction requirements. If the reconstructed data D‟ is an exact replica of the original data D, the algorithm applied to compress D and decompress c(D) is lossless. On the other hand, the algorithms are lossy when D‟ is not an exact replica of D. Hence as far as the reversibility of the original data is concerned, the data compression algorithms can be broadly classified in two categories – lossless and lossy. Usually lossless data compression techniques are applied on text data or scientific data. Sometimes data compression is referred as coding, and the terms noiseless or noisy coding, usually refer to loseless and lossy compression techniques respectively. The term “noise” here is the “error of reconstruction” in the lossy compression techniques because the reconstructed data item is not identical to the original one. Data compression schemes could be static or dynamic. In static methods, the mapping from a set of messages (data or signal) to the corresponding set of compressed codes is always fixed. In dynamic methods, the mapping from the set of messages to the set of compressed codes changes over time. A dynamic method is called adaptive if the codes adapt to changes in ensemble characteristics over time. For example, if the probabilities of occurrences of the symbols from the source are not fixed over time, an adaptive formulation of the binary codewords of the symbols is suitable, so that the compressed file size can adaptively change for better compression efficiency.

2. Discrete Cosine Transform

The discrete cosine transform (DCT) helps separate the images 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 (Figure 2)



A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as described below, fewer are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT"; its inverse, the type-III DCT, is correspondingly often called simply "the inverse DCT" or "the IDCT". Two related transforms are the discrete sine transforms (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transforms (MDCT), which is based on a DCT of overlapping data.

3. Related Work, Issues and Possible Solutions

There are many research papers that propose 1D Discrete cosine transform technique to modify an image so as to get the compressed data or image model. [1] shows a discrete wavelet technique to compress the images using wavelet theory in VHDL, Verilog. [2] shows FFT approach for data compression.that its histogram has a desired shape. [3] shows the lossless image compression algorithm using FPGA technology. [4] has shown an image compression algorithm using verilog with area, time and power constraints. [5] has shown a simple DCT technique to for converting signals into elementary frequency components using mathematica toolbox. [6] shows comparative analysis of various compression methods for medical images depicting lossless and lossy image compression. [7] shows Fourier Analysis and Image processing technique. [8] shows Image compression Implementation using Fast Fourier Transform. [9] depicts a comparative study of Image Compression using Curvelet, Ridgilet and Wavelet Transform Techniques.

4. Need for Compression

Compression is necessary in modern data transfer and processing whether it is performed on data or an image/video file as transmission and storage of uncompressed video would be extreamly costly and impractical. Framensm with 352 x 288 contains 202,752 bytes of information. Recording of uncompressed version of this video at 15 frames per second would require 3 MB. As 180 MB of data storage would be required for 1 minute and hence one 24 hours day would be utilized to store 262 GB of database.

Using Compression, at 15 frames per seconds, it takes 24 hrs. would take only 1.4GB and hence 187 days of video could be stored using the same disk space that uncompressed video would use in one day. Hence, Compression while maintaining the image quality is must for digital data, image or video file transfer in fast way and lesser amount of time.

5. Lossless and Lossy Image Compression

When hearing that image data are reduced, one could expect that automatically also the image quality will be reduced. A loss of information is, however, totally avoided in lossless compression, where image data are reduced while image information is totally preserved. It uses the predictive encoding which uses the gray level of each pixel to predict the gray value of its right neighbor. Only the small deviation from this prediction is stored. This is a first step of lossless data reduction. Its effect is to change the statistics of the image signal drastically. Statistical encoding is another important approach to lossless data reduction. Statistical encoding can be especially successful if the gray level statistics of the images has already been changed by predictive coding. The overall result is redundancy reduction, that is reduction of the reiteration of the same bit patterns in the data. Of course, when reading the reduced image data, these processes can be performed in reverse order without any error and thus the original image is recovered. Lossless compression is therefore also called reversible compression. Lossy data compression has of course a strong negative connotation and sometimes it is doubted quite emotionally that it is at all applicable in medical imaging. In transform encoding one performs for each image run a mathematical transformation that is similar to the Fourier transform thus separating image information on gradual spatial variation of brightness (regions of essentially constant brightness) from information with faster variation of brightness at edges of the image (compare: the grouping by the editor of news according to the classes of contents). In the next step, the information on slower changes is transmitted essentially lossless (compare: careful reading of highly relevant pages in the newspaper), but information on faster local changes is communicated with lower accuracy (compare: looking only at the large headings on the less relevant pages). In image data reduction, this second step is called quantization. Since this quantization step cannot be reversed when decompressing the data, the overall compression is 'lossy' or 'irreversible'.

6. Different Techniques for Image Compression

a) DFT: (Discrete Fourier Transform)

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image. The Fourier Transform is used in a wide range of applications, such as image analysis, image filtering, image reconstruction and image compression. The DFT is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. The number of frequencies corresponds to the number of pixels in the spatial domain image, i.e. the image in the spatial and Fourier domain are of the same size. For a square image of size N×N, the two-dimensional DFT is given by:

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\, e^{-\iota 2\pi(\frac{ki}{N}+\frac{lj}{N})} \quad (1)$$

where f(a,b) is the image in the spatial domain and the exponential term is the basis function corresponding to each point F(k,l) in the Fourier space. The equation can be interpreted as: the value of each point F(k,l) is obtained by multiplying the spatial image with the corresponding base function and summing the result. In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$F(k,l) = \frac{1}{N^2} \sum_{a=0}^{N-1} \sum_{b=0}^{N-1} f(a,b)\, e^{-\iota 2\pi(\frac{ka}{N}+\frac{lb}{N})} \quad (2)$$

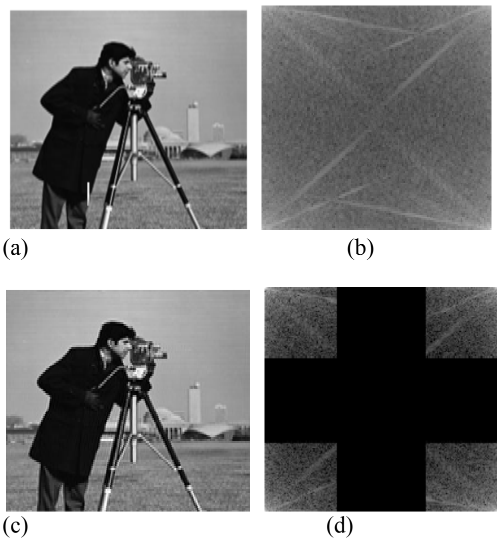
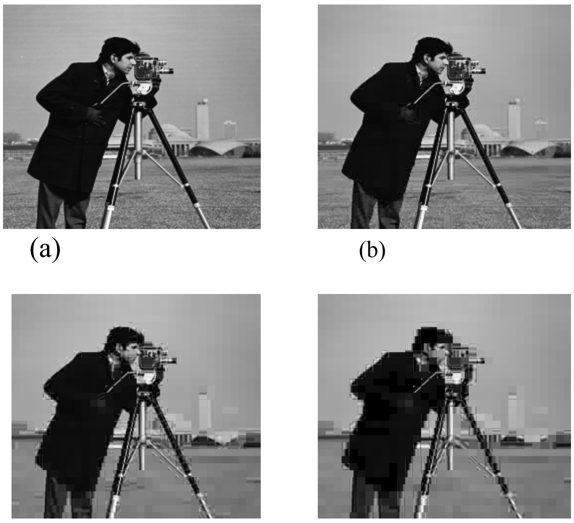


Figure 2 : a) Input Image without compression
b) and c) Discrete Fourier Transforms
d) Output Image with Inverse transform that has been constructed

b) FFT: (Fast Fourier Transform)

A fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. " There are many distinct FFT algorithms involving a wide range of mathematics, from simple complex-number arithmeticto group theory and number theory. A DFT decomposes a sequence of values into components of different frequencies. This operation is useful in many fields but computing it directly from the definition is often too slow to be practical. An FFT is a way to compute the same result more quickly: computing a DFT of N points in the naive way, using the definition, takes $O(N^2)$ arithmetical operations, while an FFT can compute the same result in only O(N log N) operations. The difference in speed can be substantial, especially for long data sets where N may be in the thousands or millions—in practice, the computation time can be reduced by several orders of magnitude in such cases, and the improvement is roughly proportional to N / log (N). This huge improvement made many DFT-based algorithms practical; FFTs are of great importance to a wide variety of applications, from digital and solving partial differential equations to algorithms for quick multiplication of large integers.



(a) (b)

(c) (d)

Figure 3:
(a) The Original Cameraman Image
(b) Cameraman Image after decompression (cut off=20, MSE=36.82) using FFT
(c) Cameraman Image after decompression (cut off=40, MSE=102.43) using FFT
(d) Cameraman Image after decompression (cut off=60, MSE=164.16) using FFT

c) DCT Algorithm And Its Advantages

The 1D DCT is defined as

$$\mathbf{D}_X\{f\}(\omega)=a(\omega)\sum_{x=0}^{N-1} f(x)\cos\left(\frac{(2x+1)\omega\pi}{2N}\right)\ ;\ a(\omega)=\begin{cases}\sqrt{\frac{1}{N}} & \omega=0\\ \sqrt{\frac{2}{N}} & else\end{cases} \qquad (3)$$

which is similar to the DFT

$$F(\omega)=\frac{1}{N}\sum_{x=0}^{N-1} f(x)e^{-\frac{j2\pi x\omega}{N}} \qquad (4)$$

2D DCT is defined using the separability property as 1D transform on the rows and on the columns, applied separately:

$$F(u,v)=\mathbf{D}_Y\{\mathbf{D}_X\{f(x,y)\}\} \qquad (5)$$

One of the advantages of DCT is the fact that it is a real transform, whereas DFT is complex. This implies lower computational complexity, which is sometimes important for real-time applications. DCT is used in some lossy compression algorithms, including JPEG. (The JPEG standard codec is more complicated, for it includes a quantizer for DCT coefficients and DPCM statistical prediction scheme. The output of the codec is the prediction error, which is encoded using some lossless entropy code.) In the transform image, DC is the matrix element (1,1), corresponding to transform value X(0,0). High spatial X and Y frequencies correspond to high column and row indexes, respectively.

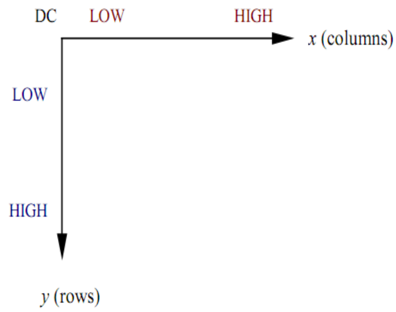


Figure 4: DCT image. Red labels denote horizontal spatial frequencies, blue label denote vertical frequencies.

According to the DCT properties, a DC is transformed to discrete delta-function at zero frequency. Hence, the transform image contains only the DC component. This can be seen in the transform image. The DC value is a sum over the whole image. The majority of the DCT energy is concentrated on low frequencies. The reason is the fact that natural images possess mostly low-frequency features and high-frequency features (edges) are rarely encountered.The advantages of DCT compression are based on the fact that most natural images have sparse edges. Hence, most blocks contain primarily low frequencies, and can be represented by a small number of coefficients without significant precision loss. Edges are problematic since are associated with high spatial frequency. Consequently, the DCT at blocks where the edges pass has high-amplitude coefficients at high frequencies, which cannot be removed without significant distortion. This effect was seen on the coin image, where small number of coefficients resulted in very significant distortion of the edges.

Images containing non-sparse edges, such as the standard MATLAB image of an integral circuit (IC), are very problematic for such compression method, since they primarily consist of edges. The compression algorithm can be significantly improved if the coefficients selection would be adaptive, i.e. in each DCT block we would select a different number of coefficients with the largest amplitude. Thus, smooth regions of an image can be represented by a small number of coefficients, whereas edges and high-frequency textures would be represented by large number of coefficients. This will solve the problem of edges, whilst leaving the algorithm efficient. The number of coefficients required for edge representation can be reduced if the idea of overcomplete base is used. Using some overcomplete basis for geometry representation (e.g. different types of edgelets, ridgelets and other geometry encoding wavelets proposed by Mallat and Donoho) it would be enough to take only several coefficients in order to represent an edge.

7. Conclusions and Future Results

In my work, I have prepared transformed the image into 8 x 8 subsets by applying DCT in 2 dimension. Also, a subset of DCT co-efficients have been prepared in order to perform inverse DCT to get the reconstructed image. The work to be done in later stages is to perform the inverse transform of the transformed image and also to generate the error image in order to give the results in terms of MSE (Mean Square Error) ,as MSE increases, the image quality degrades and as the MSE would decrease, image quality would be enhanced.

In the JPEG image compression algorithm, the input image is divided into 8-by-8 or 16-by-16 blocks, and the two-dimensional DCT is computed for each block. The DCT coefficients are then quantized, coded, and transmitted. The JPEG receiver (or JPEG file reader) decodes the quantized DCT coefficients, computes the inverse two-dimensional DCT of each block, and then puts the blocks back together into a single image. For typical images, many of the DCT coefficients have values close to zero; these coefficients can be discarded without seriously affecting the quality of the reconstructed image. An algorithm was developed for checking the image compression on an image of cameraman as shown in figure 2 a) and 3 a).

```
I = imread('cameraman.tif');
I = im2double(I);
T = dctmtx(8);
B = blkproc(I,[8 8],'P1*x*P2',T,T');
mask = [1   1   1   1   0   0   0   0
        1   1   1   0   0   0   0   0
        1   1   0   0   0   0   0   0
        1   0   0   0   0   0   0   0
        0   0   0   0   0   0   0   0
        0   0   0   0   0   0   0   0
        0   0   0   0   0   0   0   0
        0   0   0   0   0   0   0   0];
B2 = blkproc(B,[8 8],'P1.*x',mask);
I2 = blkproc(B2,[8 8],'P1*x*P2',T',T);
     imshow(I), figure, imshow(I2)
```

Figure 5: a) Original Image Of Cameramen b) Reconstructed Image after applying 8 x 8 block subset using DCT

Although there is some loss of quality in the reconstructed image, it is clearly recognizable, even though almost 85% of the DCT coefficients were discarded. To experiment with discarding more or fewer coefficients, and to apply this technique to other images, we have developed a modified algorithm using given equations:

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N}, \quad \begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1 \end{matrix}$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, & p = 0 \\ \sqrt{2/M}, & 1 \le p \le M-1 \end{cases} \qquad \alpha_q = \begin{cases} 1/\sqrt{N}, & q = 0 \\ \sqrt{2/N}, & 1 \le q \le N-1 \end{cases}$$

……………(6)

Where, M and N are the row and column size of A, respectively. If you apply the DCT to real data, the result is also real. The DCT tends to concentrate information, making it useful for image compression applications. This transform can be inverted using inverse DCT. Inverse DCT transform computes the 2 dimensional inverse DCT using:

$$A_{mn} = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} \alpha_p \alpha_q B_{pq} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N}, \quad \begin{matrix} 0 \le m \le M-1 \\ 0 \le n \le N-1 \end{matrix}$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, & p = 0 \\ \sqrt{2/M}, & 1 \le p \le M-1 \end{cases} \qquad \alpha_q = \begin{cases} 1/\sqrt{N}, & q = 0 \\ \sqrt{2/N}, & 1 \le q \le N-1 \end{cases}$$

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