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Image Compression Algorithms Using Dct

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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 and resulting performance parameter would be indicated in terms of MSE , i.e. Mean Square Error.

Keywords- Discrete Cosine Transform, Pixels, Inverse -DCT, Encoding, Decoding, Quantization, Entropy, MSE.

I. 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 understood as a method that takes an input data D and generates a shorter representation of the data c(D) with less number of bits 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”. The reconstructed data D□ could be identical to the original data d or it could be an approxima-

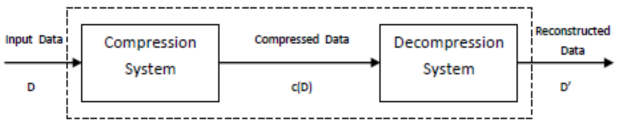

figure.1 Block Diagram of CODEC

-tion 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 loseless 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. 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.

II. DISCRETE COSINE TRANSFORM

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 2)

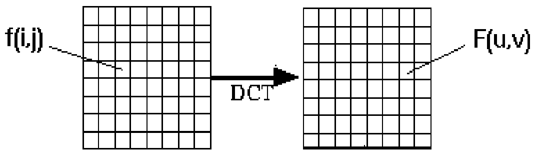

figure.2 Transformation of function into DCT

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.

III. RELATED WORK, ISSUES AND POSSIBLE SOLUTIONS

Apart of so many advantages of Discrete Wavelet Transform, Discrete wavelet transform donot justify wide replacement of DCT to avoid blocking artifacts. Discrete Cosine Transform is a technique for converting a signal into elementary frequency components, widely used in image compression. The rapid growth of digital imaging applications, including desktop publishing, multimedia, teleconferencing, and high-definition television (HDTV) has increased the need for effective and standardized image compression techniques. Among the emerging standards are JPEG, for compression of still images [Wallace 1991]; MPEG, for compression of motion video [Puri 1992]; and CCITT H.261 (also known as Px64), for compression of video telephony and teleconferencing. 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.

JPEG is primarily a lossy method of compression.JPEG was designed specifically to discard information that the human eye cannot easily see. Slight changes in color are not perceived well by the human eye, while slight changes in intensity (light and dark) are. Therefore JPEG's lossy encoding tends to be more frugal with the gray-scale part of an image and to be more frivolous with the color .DCT separates images into parts of different frequencies where less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression.

IV. PROBLEM FORMULATION

Wavelet based techniques for image compression have been increasingly used for image compression.

The wavelet uses subband coding to selectively extract different subbands from the given image.These subbands can then be quantized with different quantizers to give better compression.The wavelet filters are specifically designed to satisfy certain constraints called the smoothness constraints. The wavelet filters are designed so that the coefficients in each subband are almost uncorrelated from the coefficients in other subbands [3]. The wavelet transform achieves better energy compaction than the DCT and hence can help in providing better compression for the same Peak Signal to Noise Ratio (PSNR). A lot of research has been done on the performance comparison of the DWT and DCT for image compression which is less than 1 dB. This proposed work is to analyse the image compression algorithm using 2-dimension DCT. 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. To transformed an 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 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 with the help of changing the co-efficients for DCT Blocks.

V. WORK METHODOLOGY

Image compression is a technique used to reduce the storage and transmission costs. The existing techniques used for compressing image files are broadly classified into two categories, namely lossless and lossy compression techniques. In lossy compression techniques, the original digital image is usually transformed through an invertible linear transform into another domain, where it is highly de-correlated by the transform. This de-correlation concentrates the important image information into a more compact form. The transformed coefficients are then quantized yielding bit-streams containing long stretches of zeros. Such bit-streams can be coded efficiently to remove the redundancy and store it into a compressed file. The decompression reverses this process to produce the recovered image. The 2-D discrete cosine transform (DCT) is an invertible linear transform and is widely used in many practical image compression systems because of its compression performance and computational efficiency [10-12]. DCT converts data (image pixels) into sets of frequencies. The first frequencies in the set are the most meaningful; the latter, the least. The least meaningful frequencies can be stripped away based on allowable resolution loss. DCT-based image compression relies on two techniques to reduce data required to represent the image. The first is quantization of the image's DCT coefficients; the second is entropy coding of the quantized coefficients [13]. Quantization is the process of reducing the number of possible values of a quantity, thereby reducing the number of bits needed to represent it. Quantization is a lossy process and implies in a reduction of the color information associated with each pixel in the image. Entropy coding is a technique for representing the quantized coefficients as compactly as possible.

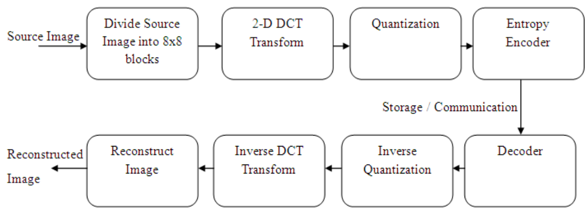

figure.3: Block Diagram For Compression/ Decompression Algorithm

In this paper, a simple entropy encoder algorithm will be proposed and implemented. It works on quantized coefficients of the discrete cosine transform. The basic idea of the new approach is to divide the image into 8x8 blocks and then extract the consecutive non-zero coefficients preceding the zero coefficients in each block. In contrast to the Run_Length decoder, the output of this encoder consists of the number of the nono-zero coefficients followed by the coefficients themselves for each block. The decompression process can be performed systematically and the number of zero coefficients can be computed by subtracting the number of non-zero coefficients from 64 for each block.

After the reconstructed image is obtained, the error image is also generated using MATLAB image processing commands by subtracting the reconstructed image from the original image and MSE (main square error) is computed to indicate the quality of the reconstructed image that is best when MSE = 0 , that happens when all the 64 co-efficients are selected in the simulations.

VI. 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'.

VII. JPEG

The DCT is used in JPEG image compression, MJPEG, MPEG, DV, and Theora video compression. There, the two-dimensional DCT-II of N x N blocks are computed and the results are quantized and entropy coded. In this case, N is typically 8 and the DCT-II formula is applied to each row and column of the block. The result is an 8 × 8 transform coefficient array in which the (0,0) element (top-left) is the DC (zero-frequency) component and entries with increasing vertical and horizontal index values represent higher vertical and horizontal spatial frequencies.

It incorporated the last advances in the image compression to provide a unified optimized tool to accomplish both lossless and lossy compression and decomposition using the same algorithm and the bit stream syntax. The systems architecture is not only optimized for compression efficiency at even very low bit-rates, it is also optimized for scalability and interoperability in the networks and noisy mobile environments. The JPEG standard will be effective in wide application areas such as internet, digital photography, digital library, image archival, compound documents, image databases, colour reprography (photocopying, printing, scanning, facsimile), graphics, medical imagery, mobile multimedia communication, 3G cellular telephony, client-server networking, e-commerce, etc.

VIII. QUANTIZATION

DCT-based image compression relies on two techniques to reduce the data required to represent the image. The first is quantization of the image's DCT coefficients; the second is entropy coding of the quantized coefficients. Quantization is the process of reducing the number of possible values of a quantity, thereby reducing the number of bits needed to represent it. Entropy coding is a technique for representing the quantized data as compactly as possible. I have developed functions to quantize images and to calculate the level of compression provided by different degrees of quantization.

IX. ENTROPY ENCODING

After quantization, most of the high frequency coefficients (lower right corner) are zeros. To exploit the number of zeros, a zig-zag scan of the matrix is used yielding to Long strings of zeros. The current coder acts as filter to pass only the string of non-zero coefficients. By the end of this process we will have a list of non-zero tokens for each block preceded by their count. DCT based image compression using blocks of size 8x8 is considered. After this, the quantization of DCT coefficients of image blocks is carried out. After that, entropy encoding technique is applied to the resulting image.

Entropy encoding is a compression method based on the idea of allotting fewer bits to represent colors that occur frequently in an image and more bits to those that occur infrequently. Shannons entropy equation, allows us to compare an encoding to a theoretical optimum.Processes with this principle are called entropy encoding. There are several of this kind. Entropy encoding is used regardless of the media's specific characteristics. The data stream to be compressed is considered to be a simple digital sequence, and the semantic of the data is ignored. Entropy encoding is an example of lossless encoding as the decompression process regenerates the data completely. The raw data and the decompressed data are identical, no information is lost.

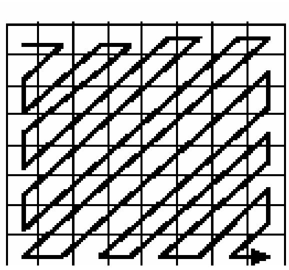

figure.4 Zigzag Sequence

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

$$F(u) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \Lambda(i).cos\left[\frac{\pi.u}{2.N}(2i+1)\right] f(i) \tag{1}$$

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

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

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

$$F(u,v) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \left(\frac{2}{M}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \Lambda(i).\Lambda(j).cos\left[\frac{\pi.u}{2.N}(2i+1)\right] cos\left[\frac{\pi.v}{2.M}(2j+1)\right].f(i,j) \tag{3}$$

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

$$\Lambda(\xi) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for}\xi = 0 \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

The basic operation of the DCT is as follows:

- The input image is N by M;
- f(i,j) is the intensity of the pixel in row i and column j;
- F(u,v) is the DCT coefficient in row k1 and column k2 of the DCT matrix.
- For most images, much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT.
- Compression is achieved since the lower right values represent higher frequencies, and are often small - small enough to be neglected with little visible distortion.
- The DCT input is an 8 by 8 array of integers. This array contains each pixel's gray scale level;
- 8 bit pixels have levels from 0 to 255.
- Therefore an 8 point DCT would be:

where,

$$\Lambda(\xi) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for}\xi = 0 \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

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X. INVERSE DCT

Using the normalization conventions above, the inverse of DCT-I is DCT-I multiplied by 2/(N-1) The inverse of DCT-IV is DCT-IV multiplied by 2/N. The inverse of DCT-II is DCT-III multiplied by 2/N and vice versa.

Like for the DFT, the normalization factor in front of these transform definitions is merely a convention and differs between treatments. For example, some authors multiply the transforms by √2/N so that the inverse does not require any additional multiplicative factor. Combined with appropriate factors of √2 (see above), this can be used to make the transform matrix orthogonal.

10.1. MULTIDIMENSIONAL DCT'S

Multidimensional variants of the various DCT types follow straightforwardly from the one-dimensional definitions: they are simply a separable product (equivalently, a composition) of DCTs along each dimension.

For example, a two-dimensional DCT-II of an image or a matrix is simply the one-dimensional DCT-II, from above, performed along the rows and then along the columns (or vice versa). Technically, computing a two- (or multi-) dimensional DCT by sequences of one-dimensional DCTs along each dimension is known as arow-column algorithm (after the two-dimensional case). That is, the 2d DCT-II is given by the formula (omitting normalization and other scale factors, as above):

$$\begin{aligned} X_{k_1,k_2} &= \sum_{n_1=0}^{N_1-1} \left(\sum_{n_2=0}^{N_2-1} x_{n_1,n_2} \cos\left[\frac{\pi}{N_2}\left(n_2+\frac{1}{2}\right)k_2\right]\right) \cos\left[\frac{\pi}{N_1}\left(n_1+\frac{1}{2}\right)k_1\right] \\ &= \sum_{n_1=0}^{N_1-1} \sum_{n_2=0}^{N_2-1} x_{n_1,n_2} \cos\left[\frac{\pi}{N_1}\left(n_1+\frac{1}{2}\right)k_1\right] \cos\left[\frac{\pi}{N_2}\left(n_2+\frac{1}{2}\right)k_2\right]. \end{aligned} \tag{6}$$

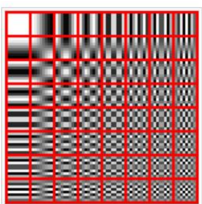


figure 5: Two-dimensional DCT frequencies from the JPEG DCT

As with multidimensional FFT algorithms, however, there exist other methods to compute the same thing while performing the computations in a different order (i.e. interleaving/combining the algorithms for the different dimensions). The inverse of a multi-dimensional DCT is just a separable product of the inverse(s) of the corresponding one-dimensional DCT(s) (see above), e.g. the one-dimensional inverses applied along one dimension at a time in a row-column algorithm.The image to the right shows combination of horizontal and vertical frequencies for an 8 x 8 ($N_1 = N_2 = 8$) two dimensional DCT. Each step from left to right and top to bottom is an increase in frequency by 1/2 cycle. For example, moving right one from the top-left square yields a half-cycle increase in the horizontal frequency. Another move to the right yields two half-cycles. A move down yields two half-cycles horizontally and a half-cycle vertically. The source data (8x8) is transformed to a linear combination of these 64 frequency squares

XI. MSE: MEAN SQUARE ERROR

The phrase Mean Square Error, often abbreviated MSE (also called PSNR, Peak Signal to Noise Ratio) is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, MSE is usually expressed in terms of the logarithmic decibel scale.

The MSE / PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (7)$$

The PSNR is defined as:

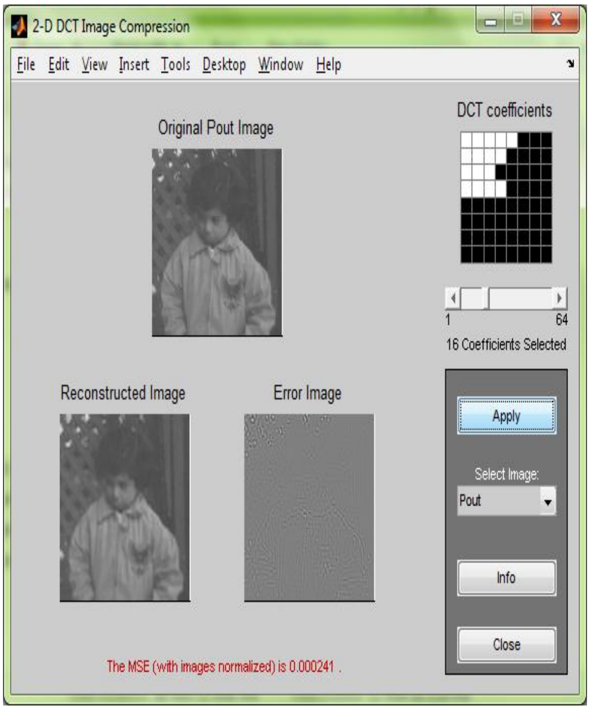
$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \end{aligned} \qquad (8)$$

Here, MAX_I 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, MAX_I is $2B-1$. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three.

figure.6: Example luma PSNR values for a cjpeg compressed image at various quality levels

XII.SIMULATIONS AND RESULTS

The window shows the original image, reconstructed image after applying 2D – DCT and the computed error image. On the right hand side, top is shown a slider option to vary the number of coefficients of 8 x 8 blocks image input for DCT matrix that could have a value in between 1 to 64. Apply button is present to finally apply the DCT on the image selected after setting the number of co-efficients for the image compression. Also, MSE is calculated and displayed on the bottom of the images indicating the quality of reconstructed image.In the above picture, all the 64 co-efficients have been selected and error image is obtained zero with mean square error value i.e. MSE = 0 indicating that best reconstruction is attained at highest number of co-efficients has been selected. The window for showing the results that appear on the screen when running the code is shown below:



Analysis of Image Compression Algorithm using DCT is conducted on Six natural images out of which Pepper Image has been shown before and after reconstruction along with their obtained MSE.

a) Original Image

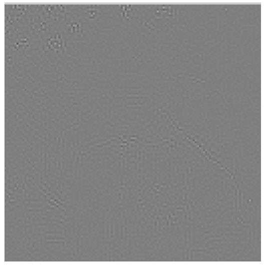
After DCT (25%) : DCT Coefficients selected = 16

b) Reconstructed Image c) Error Image

Mean Square Error = 0.000241

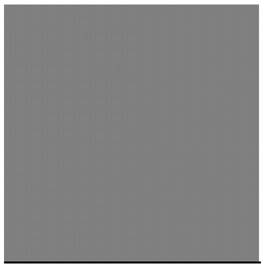
After DCT (50%) : Coefficients selected = 32

d) Reconstructed Image e) Error Image

Mean Square Error = 7.62e-005

After DCT (100%) : Coefficients selected = 64

f) Reconstructed Image g) Error Image

Mean Square Error = 0.0

In the above picture, all the 64 co-efficients have been selected and error image is obtained zero with MSE = 0 indicating that best reconstruction is attained at highest number of co-efficients been selected

XIII. FUTURE SCOPE AND CONCLUSIONS

The results presented in this document show that the DCT exploits interpixel redundancies to render excellent decorrelation for most natural images. Thus, all (uncorrelated) transform coefficients can be encoded independently without compromising coding efficiency. In addition, the DCT packs energy in the low frequency regions. Therefore, some of the high frequency content can be discarded without significant quality degradation. Such a (course) quantization scheme causes further reduction in the entropy (or average number of bits per pixel). Lastly, it is concluded that successive frames in a video transmission exhibit high temporal correlation (mutual information). This correlation can be employed to improve coding efficiency.

The aforementioned attributes of the DCT have led to its widespread deployment in virtually every image/video processing standard of the last decade, for example, JPEG (classical), MPEG- 1, MPEG-2, MPEG-4, MPEG-4 FGS, H.261, H.263 and JVT (H.26L). Nevertheless, the DCT still offers new research directions that are being explored in the current and upcoming image/video coding standards.

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