

Image Compression Algorithms under JPEG with Lapped Orthogonal Transform and Discrete Cosine Transformation

Anurag Bhatt¹, Dr. Ashutosh Kumar Bhatt²

¹M.Tech CSE Department, Uttarakhand Technical University, Dehradun (Uttarakhand), India

²Associate Professor. CSE Dept, Birla Institute of Applied Sciences (BIAS), Bhimtal Uttarakhand - India

Abstract:- This Paper Focus On Image Compression. It is used specially for the compression of images where tolerable degradation is required. With the wide use of computers and consequently need for large scale storage and transmission of data, efficient ways of storing of data have become necessary. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. JPEG and JPEG 2000 are two important techniques used for image compression. JPEG image compression standard use dct (discrete cosine transform). Now here Lapped Orthogonal Transform and Discrete Cosine Transformation are using with JPEG 2000 standard. The discrete cosine transform is a fast transform. It is a widely used and robust method for image compression. It has excellent compaction for highly correlated data. DCT has fixed basis images DCT gives good compromise between information packing ability and computational complexity

Keywords:- JPEG, JPEG2000, DCT

I. INTRODUCTION

An image may be defined as a two-dimensional function $f(x, y)$, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point [8]. When x, y , and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used to denote the elements of a digital image.

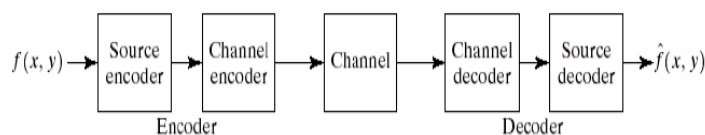


Fig1: General compression model

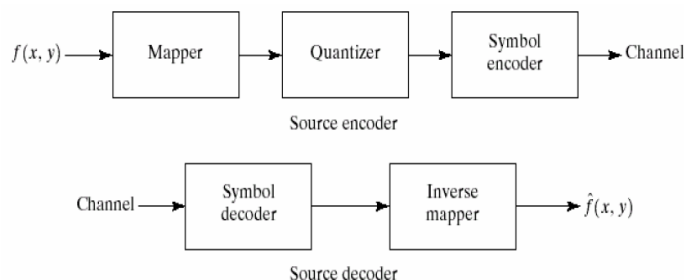


Fig2: a) Source encoder model **b)** Source decoder model

II. CLASSIFICATION OF IMAGE COMPRESSION SCHEMES

Image compression using transform coding yields extremely good compression, with controllable degradation of image quality. These are:

- Lossless technique
- Lossy technique

A. Lossless compression technique:

In lossless compression techniques, the original image can be perfectly recovered from the compressed (encoded) image. These are also called noiseless since they do not add noise to the signal (image). It is also known as entropy coding since it uses statistics/decomposition techniques to eliminate/minimize Redundancy. Lossless compression is used only for a few applications with stringent requirements such as medical imaging. Following techniques are included in lossless compression:

1. Run length encoding
2. Huffman encoding
3. LZW coding
4. Area coding

B. Lossy compression technique:

Lossy schemes provide much higher compression ratios than lossless schemes. Lossy schemes are widely used since the quality of the reconstructed images is adequate for most applications. By this scheme, the decompressed image is not identical to the original image, but reasonably close to it. In this prediction – transformation – decomposition process is completely reversible. The quantization process results in loss of information. The entropy coding after the quantization step, however, is lossless. The decoding is a reverse process. Firstly, entropy decoding is applied to compressed data to get the quantized data. Secondly, dequantization is applied to it & finally the inverse transformation to get the reconstructed image. Major performance considerations of a lossy compression scheme include:

1. Compression ratio
2. Signal - to - noise ratio
3. Speed of encoding & decoding.

Lossy compression techniques include following schemes:

1. Transformation coding
2. Vector quantization
3. Fractal coding
4. Block Truncation Coding
5. Subband coding

III. LAPPED ORTHOGONAL TRANSFORMATION

The Lapped Orthogonal Transform denotes a lapped transform whose input length is equal to twice its output length ($L = 2M$). Previous research showed the LOT is more appropriate for image coding, comparing with other lapped transforms, because the LOT achieves higher compression efficiency for images and has less computational cost. 2.2.2. Design of the LOT In order to make the design of LOT robust, we can begin with a family of valid LOTs. Then, the optimal LOT within this family or subspace can be found. Our first valid LOT matrix is P_0 . Input image is first portioned into 8×8 non overlapping blocks, and then 16×16 overlapping blocks are obtained as shown in fig 2, since, direct computation of 2D LOT and its inverse requires large computation time, a computationally efficient method described below, is used.

$$F = P_t X P = Z_t P$$

Where $Z = X_t P$ and Z_t is its transpose. X and F are 16×16 input pixel and 8×8 coefficient matrix

IV. DISCRETE COSINE TRANSFORM

A 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 [8][9].

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 k_1 and column k_2 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 .

V. PURPOSE ALGORITHM

Step 1: Read Input image

<pre>Read the input image of size 512x512 using imread function take a quality factor quality = [10:5:90,93]; After set the value of delta for the different transformation del = flip ([2,5,3,4,5,6, 8,10,13,16,20 ,25, 30,35, 40,50 ,60]);</pre>	
<p style="text-align: center;">A : input image</p>	

Step 2: image to columns

Rearrange image blocks into columns. Image size of 512X512 now arranges in single column i.e.272144 and transformation is applied.

$B = \text{im2col}(A, [m \ n], \text{block_type})$

Rearranges image blocks into columns. `block_type` is a string that can have one of these values. The default value is enclosed in braces ({})

```
>> whos X
Name      Size      Bytes Class  Attributes
X         1x262144  2097152 double
```

Step 3: Apply the Quantization and inverse Quantization technique using the threshold values.

Quantization leads to a compression of the image. Indeed, with a fixed length binary code, 8 bits per pixel are needed to code 256 colors and 4 bits per pixel to code 16 colors. We notice that the image obtained after quantization is of good quality. However, within the framework of true compression, quantization is not used on the original image, but on its wavelet decomposition.

Step4 : Apply the inverse Quantization technique without any threshold values

Step 5: Rearrange matrix columns into blocks

$A = \text{col2im}(B, [m \ n], [mm \ nn], 'distinct')$ rearranges each column of B into a distinct m-by-n block to create the matrix A of size mm-by-nn. If $B = [A11(:) \ A21(:) \ A12(:) \ A22(:)]$, where each column has length m*n, then $A = [A11 \ A12; \ A21 \ A22]$ where each A_{ij} is m-by-n.

$A = \text{col2im}(B, [m \ n], [mm \ nn], 'sliding')$ rearranges the row vector B into a matrix of size (mm-m+1)-by-(nn-n+1). B must be a vector of size 1-by-(mm-m+1)*(nn-n+1). B is usually the result of processing the output of $\text{im2col}(\dots, 'sliding')$ using a column compression function (such as sum).

$\text{col2im}(B, [m \ n], [mm \ nn])$ is the same as $\text{col2im}(B, [m \ n], [mm \ nn], 'sliding')$.

Step 6: the Lapped Orthogonal Transform and Discrete Cosine Transformation

Image divided into 3 sections and apply the Lapped Orthogonal Transform and Discrete Cosine Transformation simultaneously.

Step 7: restructure between matrix and unit range of sequences

Find the Synthesis matrix for the lapped orthogonal and Discrete Cosine Transformation and then use the concept of reshape.

$B = \text{reshape}(A, m, n)$ returns the m-by-n matrix B whose elements are taken column-wise from A.

Step 8: Estimate bits for coding a cell-array of integer sequences

this estimate bits based on zero-order entropy of each sequence and entropy coding method is Huff6.

$E = \text{entropy}(I)$ returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as $-\sum(p_i \cdot \log_2(p_i))$

where p contains the histogram counts returned from `imhist`. By default, entropy uses two bins for logical arrays and 256 bins for `uint8`, `uint16`, or `double` arrays.

It can be a multidimensional image. If I has more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image.

Step9: find out the bits and calculate the total bytes

```
a = numel(find(counts));
e = entropy0(counts);
b = ceil(numel(xC{i})*e) + ceil(a*log2(a));
```

Step 10 : Find out bit rate on the basic of transformation the

Bit rate = [0.25, 0.5, 0.75, 1.0, 1.25, 1.50, 1.75, 2.0];

Step 11: Calculation of PSNR:

```
R=double(input image+128)-compressed image;
PSNR = 10*log10(((numel(A)*peak^2)/sum(sum(R.*R))));
```

VI RESULTS

A. Peak Signal to Noise Ratio (PSNR) and Comparison

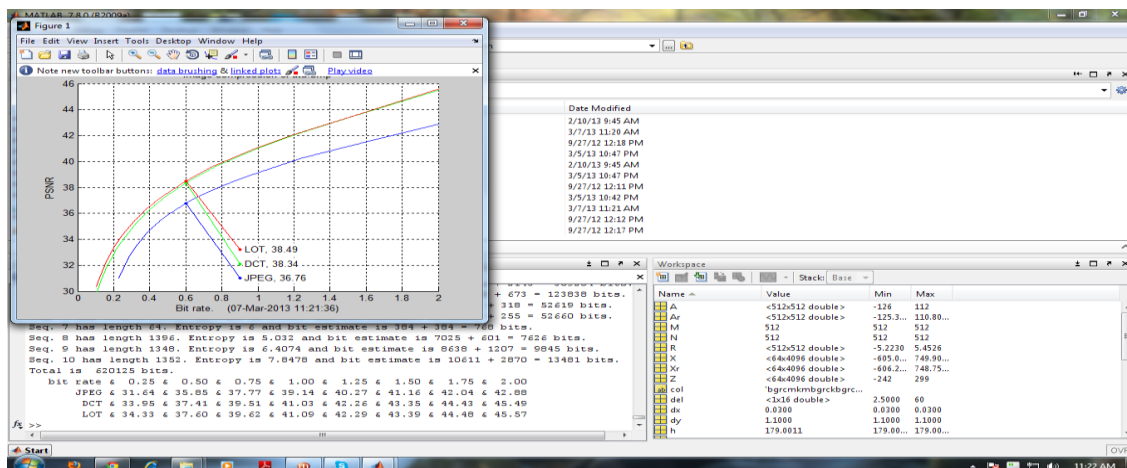
The results of table 1 have been compared with conclusion from here is the value of PSNR is good of our proposed method for bit rates 0.6 (bpp).

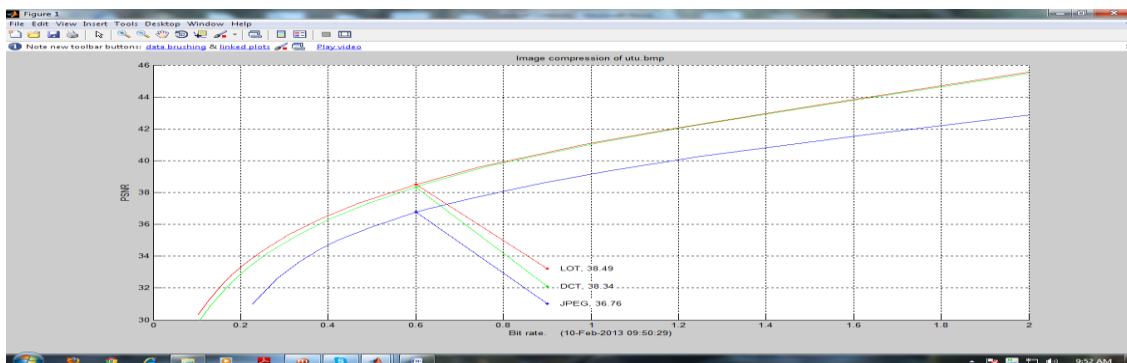
Table 1: comparison study

Transformation	PSNR
DCT	38.49
LOT	38.34
Hybrid(JPG)	36.76

The proposed coding scheme has been simulated on a pc with matlab. The original image 512x512, 256 gray level test image utu.bmp and size is 257 kb and after apply the hybrid technique after compressed image size is 64.4 kb and dimension is 512x512 with PSNR 36.76 at bit rates (bits per pixel, bpp) 0.6. The PSNR(db) of the reconstructed images were recorded as a function of bit rate in bits per pixel (bpp), which is determined from the actual size in bytes from the compressed files.

The principles and performance of the Lapped Orthogonal Transform and Discrete Cosine Transformation are discussed here. Lapped Orthogonal Transform and Discrete Cosine Transformation delivers higher quality images at various bit rates than the traditional DCT transform coding schemes. Extremely low bit rate as 0.10 bpp or 0.15 bpp has little importance for implementations. Compressing images in the range of rates from 0.25 to 0.75 bpp seems to be the ideal place to enjoy the advantage of the Lapped Orthogonal Transform and Discrete Cosine Transformation On the other hand, this scheme only increases computational cost by a small amount over that of the DCT





VII CONCLUSION

In this Paper image compression techniques using DCT and LOT were implemented. DCT is used for transformation in JPEG standard. DCT performs efficiently at medium bit rates. Disadvantage with DCT is that only spatial correlation of the pixels inside the single 2-D block is considered and the correlation from the pixels of the neighboring blocks is neglected. Blocks cannot be decor related at their boundaries using DCT. DCT is used as basis for transformation in JPEG 2000 standard. DCT provides high quality compression at low bit rates.

Though the DCT-based image compression method performs well at moderate bit a rate, the image quality degrades rapidly at higher compression ratios. This is due to the artifacts resulting from the block-based DCT scheme. On the contrary, dct and lot based compression technique provides substantial enhancement in picture quality at low bit rates due to overlapping basis functions and better energy compaction property of wavelet transforms. This thesis presents some mathematical background of compression technique mainly based on the transformation as well as the compression method.

We have introduced a block-based image compression algorithm capable of exploiting the transformation technique. For this purpose, we presented a transform design method that jointly optimizes the classification of blocks and corresponding transforms lot and dct. The result is a set of optimal transforms that replace the traditional block transforms used in image compression. The geometry information is used only at the initialization of the transform optimizations. Our compression results show PSNR against thee bits rate based on entropy method Huffo6.

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