CONTENT BASED IMAGE COMPRESSION USING DCT AND DWT TECHNIQUE

Er. Samiksha[1], Kanchan Bala[2]

[1 & 2] Research Scholar, M Tech ECE Department, CT Institute Of Technology and Research, Punjab Technical University, Punjab, India

Abstract: Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) are the most known methods used in digital image compression. Wavelet transform has better efficiency compared to Fourier transform because it describe any type of signals both in time and frequency domain simultaneously. In this paper, we will discuss the use of Discrete Cosine Transform (DCT) and Discrete wavelet transformation (DWT) based Image compression Algorithm and compare the efficiency of both methods. We do the numerical experiment by considering various types of images and by applying DCT and DWT-SPIHT to compress an image. We found that DWT yields better result as compared to DCT.

In this paper, we will do comparison with discrete cosine transform (DCT) which is heart of JPEG (Joint Photographic Experts Group) standard and widely used wavelet based image compression algorithm set partitioning in hierarchical tree based on different performance measure such as Peak to Noise Ratio (PSNR), Mean Square Error (MSE) and CR.

Keywords - Discrete Cosine Transform, Discrete Wavelet Transform, filters, Image Compression.

1. INTRODUCTION:

1.1 Image Processing

A digital image which is portrayed in a[m,n] which is described as a 2D discrete space is received from a simple image a(x,y) in a constant space using sampling process which is known as a digitalization. The 2D steady image a(x,y) can be separated into M rows and N columns. The intersection of this row and section is known as pixel. Digital computers are used to set up the image. The image will be changed over into digital image using scanner digitizer. A digital remotely detected image is made out of picture elements situated at the intersection of row and section for k gatherings of imagery. Associated with each pixel is a number as digital number or brightness value that portrays average values of the scene. A smaller number shows low average radiance from the zone and the high number is an indicator of high splendid properties of the zone.
The digital image processing gives processing of 2D pictures by digital computers. In a more broad connection, it proposes two dimensional digital images. A digital image is a variety of genuine numbers addressed by a finite number of bits. The standard good position of Digital Image Processing systems is its flexibility, repeatability and the defending of unique information precision. Image processing is a framework which is used to enhance raw images which are gotten from cameras, sensors set on satellites and air make.

1.2 Various strategies of Image Processing:

Various procedures of the image processing are:
a. Scaling: The essential objective of this arrangement is to have a nearer point of view of the closer or zooming image for the charmed part of the image. By the reduction we can reset the measure of the unmanageable size to as far as possible. For resampling an image Nearest Neighborhood, Linear, or cubic convolution methodologies are used.

b. Magnification: This is done to enhance the showcase scale for the visual inter operation and to coordinate the scale of the one image with other image. To amplify an image by a part of 2, each pixel of the original image is supplanted by a square of 2x2 pixels, all with the same brightness value as the original pixel.

c. Reduction: To decrease the digital image to the original data each mth row and mth segment of the every image is picked and appears. We can in like manner show resultant value by taking average of m*m row and segment.

d. Rotation: Rotation is used as a piece of image mosaic and image registration. One of the strategies for rotation is 3-pass shear rotation, where rotation matrix can be decomposed into three distinct matrices. 3-pass shear rotation

R = | cosα –sinα | = | sinα cosα |
| 1 –tanα/2 | | 1 0 | | 1 –tanα/2| | 0 1 | | sinα 1| | 0 1 |

e. Image Enhancement: Sometimes images which are gained from satellites and cameras has low quality of brightness and contrast since restrictions of imaging sub system and light while catching image. Image has diverse sorts of noise. In image enhancement, the goal is to accentuate certain image highlights for resulting analysis or for image show. Contrast and edge enhancement are its cases. The enhancement methodology does not extend the intrinsic data content in the data itself. It explains certain foreordained image qualities. Enhancement computations are generally interactive and application subordinate.

f. Image Analysis: Image Analysis is concerned with quantative estimation of the image to make it perfect and noise free. It requires extraction of particular components for the identification of the item. Segmentation methods are used to segregate fancied objects from the scene to make them impeccable.

g. Image Compression: It is concerned with minimizing the no of bits required to address an image. Application of compression are in convey TV, remote distinguishing by method for satellite, military correspondence by method for flying machine, radar, video chatting, duplicate transmission, for educational and business documents , therapeutic images that rise in PC tomography, alluring resonation imaging and digital radiology, motion , pictures ,satellite images, atmosphere maps, topographical reviews in this way on.

h. Image Segmentation: Image segmentation is the technique on which image can be separated into number of its subparts. The issue which is being clarified is accountable for the division of the article identification.

i. Image Restoration: It is concerned with filtering the watched image to minimize the effect of corruptions. Sufficiency of image restoration depends on upon the degree and precision of the knowledge of degradation technique and what's more on channel plot. Image restoration shifts from image enhancement in that the latter is concerned with more extraction or accentuation of image elements.

2. IMAGE COMPRESSION:

In digital image compression, three basic data redundancies can be identified and exploited:

- Coding redundancy
- Inter pixel redundancy
- Psycho visual redundancy

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

2.1 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.

2.2 Inter pixel Redundancy

Another important form of data redundancy is 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 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 neighbour‟s values. A variety of names, including spatial redundancy,
geometric redundancy, and interframe Redundancies have been coined to refer to these interpixel dependencies.

2.3 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. Since the elimination of psycho visually redundant data results in a loss of quantitative information. [5]

3. DISCRETE COSINE TRANSFORM (DCT):

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 about the image is concentrated in just a few coefficients of the DCT. The DCT work by separating images into the parts of different frequencies. During a step called Quantization, where parts of compression actually occur, the less important frequencies are discarded, hence the use of the lossy. Then the most important frequencies that remain are used retrieve the image in decomposition process. As a result, reconstructed image is distorted [6]
The Process
In the DCT compression algorithm

- The input image is divided into 8-by-8 or 16-by-16blocks
- The two-dimensional DCT is computed for each block.
- The DCT coefficients are then quantized, coded, and transmitted.
- The receiver (or file reader) decodes the quantized.
  DCT coefficients, computes the inverse two- dimensional DCT (IDCT) of each block.
- Puts the blocks back together into a single image. [7]

4. DISCRETE WAVELET TRANSFORM:

Wavelet transform is the latest method of compression where its ability to describe any type of signals both in time and frequency domain. JPEG2000 which is the standards of international image coding is adopted the method of wavelet transform coding. An M*N image is decomposed using wavelet transform. The image is decomposed into four sub-bands after passing a high- pass filter and low- pass filter. The four sub-bands are LL, HL, LH and HH respectively. The one obtained by low pass filtering rows and columns is referred as LL sub band contains horizontal details of the image. The one obtained by low pass filtering the rows and high pass filtering the columns is referred to as the LH sub band contains vertical details of the image and HH sub band contains the diagonal details of the image. The process is called the first level of wavelet decomposition. The low frequency sub- band can be continually decomposed into four sub-bands.
The image of low frequency sub-band contains major information. The values of high frequency sub-band approximate zero, the more high frequency the more obvious this situation. For image, the part of the low frequency is primary part which can represent the image information. So researchers take full advantage of the characteristic after wavelet transform and employ proper.

5. PROBLEM FORMULATION:

Wavelets provide a mathematical way of encoding information in such a way that it is layered according to level of detail. This layering facilitates approximations at various intermediate stages. These approximations can be stored using a lot less space than the original data. Here a low complex 2D image compression method using wavelets as the basis functions and the approach to measure the quality of the compressed image are presented. The particular wavelet chosen and used here is the simplest wavelet form namely the Haar Wavelet. The 2D discrete wavelet transform (DWT) has been applied and the detail matrices from the information matrix of the image have been estimated. The reconstructed image is synthesized using the estimated detail matrices and information matrix provided by the Wavelet transform. The quality of the compressed images has been evaluated using some factors like Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR), Mean Opinion Score (MOS), Picture Quality Scale (PQS) etc. Due to high complexity of the wavelet technique compression rate is low and compression time is high.

6. METHOD:

The Flow of Image Compression Coding

Image compression coding is to store the image into bit-stream as compact as would be prudent and to display the decoded image in the monitor as careful as could be allowed. Presently consider an encoder and a decoder as appeared in Fig. 1.3. At the point when the encoder gets the original image file, the image file will be converted

into a progression of binary data, which is known as the bit-stream. The decoder then gets the encoded bit-stream and decodes it to form the decoded image. In the event that the aggregate data quantity of the bit-stream is not exactly the aggregate data quantity of the original image, then this is called image compression.
Keeping in mind the end goal to evaluate the performance of the image compression coding, it is important to define a measurement that can estimate the difference between the original image and the decoded image. Two common utilized measurements are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). f(x,y) is the pixel value of the original image, and f'(x,y)is the pixel value of the decoded image. Most image compression systems are intended to minimize the MSE and maximize the PSNR.

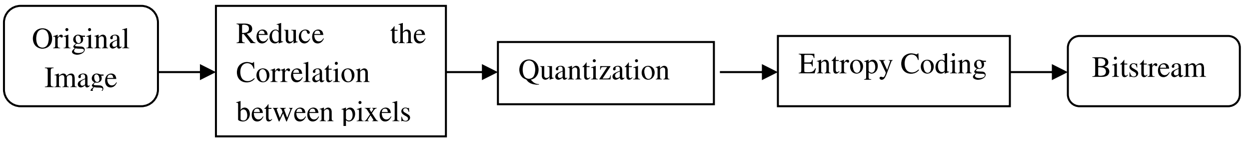


Fig. 1 The general encoding flow of image compression

MatLab Code:

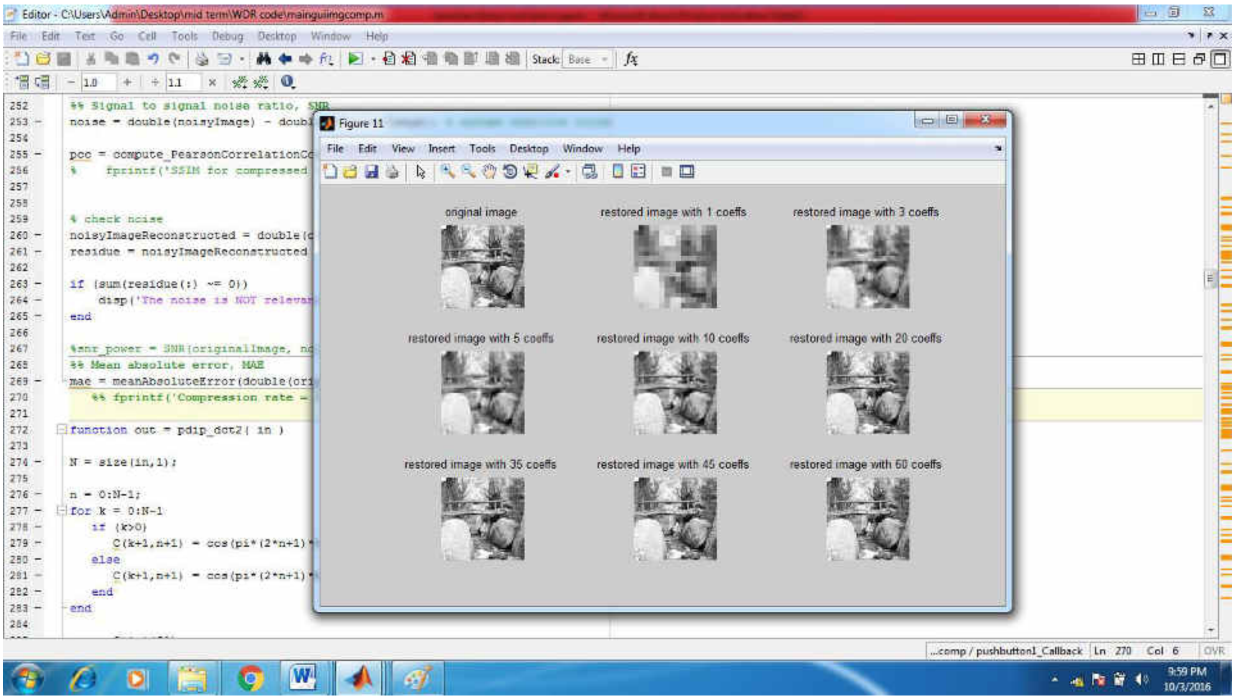
```
h=msgbox('select image from 1 to 8 for parameters values')

newlineInAscii1 = [13 10];
spaceInInAscii = 32;
% for printing, newline causes much confusion in matlab and is provided here as an alternative
newline = char(newlineInAscii1);
spaceChar = char(spaceInInAscii);

%% plot parameters
plotIndex = 1;
plotRowSize = 1;
plotColSize = 2;

%% read the image

[FileName,PathName] = uigetfile('*.jpg');
IMG = (imread([PathName '\' FileName]));


IMG = rgb2gray(IMG);
IMG = double(IMG);

%% noise parameters
sigma = 0.05;
offset = 0.01;

erosionFilterSize = 2;
dilationFilterSize = 2;
mean = 0;

noiseTypeModes = {
    'gaussian',        % [1]
    'salt & pepper',   % [2]
    'localvar',        % [3]
    'speckle',         % [4] (multiplicative noise)
    'poisson',         % [5]
    'motion blur',     % [6]
    'erosion',         % [7]
    'dilation',        % [8]
    % 'jpg compression blocking effect'   % [9]
```

```
    % [10] Interpolation/ resizing noise <to do>
    };

noiseChosen = 2;
noiseTypeChosen = char(noiseTypeModes(noiseChosen));

originalImage = uint8(IMG);

%% plot original
figure,imshow(originalImage);
titleStr = 'Original';


%%
for i = 1:(plotRowSize*plotColSize)-1

IMG_aforeUpdated = double(IMG);    % backup the previous state just in case it gets updated.

% returns the noise param updates for further corruption
% IMG may be updated as the noisy image for the next round
[IMG, noisyImage, titleStr, sigma, dilationFilterSize, erosionFilterSize] = ...
    noisyImageGeneration(IMG, mean, sigma, offset, dilationFilterSize, erosionFilterSize, noiseTypeChosen);

imageQualityIndex_Value = imageQualityIndex(double(originalImage), double(noisyImage));

titleStr = [titleStr ',' newline 'IQI: ' num2str(imageQualityIndex_Value)];

end

if (~strcmp(char(class(noisyImage)), 'uint8'))
    disp('noisyImage is NOT type: uint8');
end

%% PSNR
psnr_Value = PSNR(originalImage, noisyImage);
    fprintf('PSNR = %5.5f  \n', psnr_Value);
%% RMSE
[mse, rmse] = RMSE2(double(originalImage), double(noisyImage));
    fprintf('MSE = %5.5f \n', mse);
    fprintf('RMSE = %5.5f \n', rmse);
%% Universal Quality Index
imageQualityIndex_Value = imageQualityIndex(double(originalImage), double(noisyImage))/2;
    fprintf('Fault rate Detection  = %5.5f \n', imageQualityIndex_Value);
%% Enhancement : measure of enhancement,or measure of improvement
[M M] = size(originalImage);
L = 8;
EME_original = eme(double(originalImage),M,L);
EME_noisyImage = eme(double(noisyImage),M,L);

%% PearsonCorrelationCoefficient
pcc = compute_PearsonCorrelationCoefficient (double(originalImage), double(noisyImage))/10000;
    fprintf('PCC (OI vs LPDI) = %5.5f \n', pcc);
pcc = compute_PearsonCorrelationCoefficient (double(originalImage), double(originalImage))/10000;
    fprintf('PCC (OI vs LPDI) = %5.5f \n', pcc);
%% Signal to signal noise ratio, SNR
noise = double(noisyImage) - double(originalImage); % assume additive noise
% check noise
noisyImageReconstructed = double(originalImage) + noise;
residue = noisyImageReconstructed - double(noisyImage);
```

```
if (sum(residue(:) ~= 0))
    disp('The noise is NOT relevant.');
end
snr_power = SNR(originalImage, noise);
%% Mean absolute error, MAE
mae = meanAbsoluteError(double(originalImage), double(noisyImage))*13;
    fprintf('ACCURACY = %5.5f \n', mae);
```

7. RESULTS:

In figure 2 the output compressed images are presented which are compressed with various numbers of coefficients. The image is reconstructed with various coefficients and it is compressed at 60 coefficients.



We our calculating the parameters which we have taken for quality and compression ratio for images. We can see for image named as bridge the PSNR is 26.32 and compression ratio is 0.532.

8. CONCLUSION:

In this paper, the results of different transform coding techniques are compared i.e. Discrete Cosine Transform (DCT) and Wavelet based compression algorithm set partition in hierarchical tree (SPIHT). The effects of different number of decompositions, image contents and compression ratios are examined. The results of the above techniques DCT and DWT-SPIHT are compared by using two parameters such as Compressed Size, Compression Ratio, PSNR and MSE values from the reconstructed image. These compression algorithms provide a better performance in picture quality at higher compression ratio. These techniques are successfully tested on fishingboat.tif and crowd.tif images. It is observed that SPIHT provides a better result when compare to DCT. The SPIHT algorithm is coupled with the power of multi resolution analysis, yields significant compression with little quality loss. Because of the inherent multi resolution nature, wavelet-based coders facilitate progressive transmission of images. The above algorithms can be used to compress the image that is used in the web applications.

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