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Computations of Image Compression Using Haar Wavelet Transform to Reduce Redundancy at Different Levels

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Abstract: Every day, tremendous number of captured images must be stored and/or transmitted. The repetitive data in the images can be lessened utilizing image compression technique. Image compression prior to storage or transmission will lessen the memory byte size of images which in turn reduces the transmission bandwidth. The compressed image is reconstructed to retain the original image at the receiving end by the inverse process. In this paper, Haar Wavelet Transformation is utilized for image compression and reconstruction. This method is a basic type of lossy compression technique that permits data to be encoded according to "levels of detail". Compression ratio, Peak signal to noise ratio, Bits per pixel and relative data redundancy of different levels of image compression are compared.

Keywords: Haar wavelet transform, level of detail, compression ratio, Peak signal to noise ratio, Bits per pixel, relative data redundancy.

I. INTRODUCTION

Image compression techniques are used to reduce redundant information in images. The reduction of redundant data will in turn reduces the amount of memory bytes required to store images, transmission bandwidth required to transmit images are reduced, probability of transmission errors are reduced, cost associated with the transmission of images are reduced as bandwidth is reduced and also provides security for the transmitted image. The redundancies of image can be classified into three types, coding redundancy, interpixel redundancy and psychovisual redundancy. Coding redundancy is present due to insufficient code words used to represent an image. Interpixel redundancy is due to correlations between the pixels of an image. Psychovisual redundancy is the smallest details of an image that is ignored by human visual system. A complete image compression system generally consists of two distinct blocks, an encoder at the transmission end and a decoder at the receiving end. Image to be compressed is fed into the encoder, which encodes the image into a set of symbols. The encoded image is reconstructed at the receiving end.

Image compression techniques have been classified into two types.

1. Lossless compression:
The image compression technique in which the original image and the reconstructed image is exactly the same is known as lossless compression. The different lossless compression techniques are Run-length encoding, Huffman encoding, LZW coding and Area coding.

2. Lossy compression
The image compression technique in which the original image and the reconstructed image is not exactly the same is known as lossy compression. The different lossy compression techniques are Transformation coding, Vector quantization, Fractal coding, Block Truncation Coding and Sub-band coding.

Image compression in transform domain using wavelets is one of the popular compression techniques [1]. The wavelet transforms generated from their respective orthogonal transforms are proven to be better as compared to orthogonal transforms [2]. Previous work has shown that the Haar Wavelet Transformation (HWT) is a simple form of compression involved in averaging and differencing terms, storing detail coefficients, eliminating data, and reconstructing the matrix [2]. Different lossless image compression algorithms are compared and the maximum compression ratio achieved is 1.7908[3]. In this paper, Haar wavelet transform for image compression and decompression is discussed.

II. IMPLEMENTATION OF HAAR WAVELET TRANSFORM

Haar wavelet transform allows information to be encoded according to "levels of detail" [4]. The transformation is based on averaging and differencing values in an image matrix to produce a matrix which is sparse or nearly sparse. The transformation process will occur in N steps for $2^N X 2^N$ matrix. A sparse matrix can be stored in an efficient manner, leading to smaller file sizes. The image is decompressed using the inverse Haar wavelet transform which results with an image that is visually similar to the original image.

A. Algorithm

For compression, the image matrix is computed row-wise first followed by column-wise computation. Overview of the matrix computation to achieve compression is as follows

i) Consider two adjacent samples each time and find the average.
ii) Find the difference between each averaged value and first sample of each pair.
iii) Fill first half of the array with averages.
iv) Fill next half of the array with differences.
v) Normalize (rearrange) the matrix array.
vi) Repeat the above process (step i to step v) for first half of the rearranged array. The process is repeated N times for $2^N X 2^N$ matrix and at the end of this process only a single averaged value is left in the first entry of array.

For reconstruction, computation is first done column-wise followed by row-wise computation. The procedure followed for reconstruction is as follows

i) Find sum and difference of the averaged value and corresponding detail coefficient.
ii) Fill the array with sum and difference.
iii) Normalize (rearrange) the matrix array.
iv) Repeat the above procedure (step i to iii) for the rearranged array. The process is repeated N-1 times for $2^N X 2^N$ matrix and at the end of this process all the added and subtracted values are present in the array.

B. Quality Measurement

The parameters used to assess the quality of image compression is as follows

a) Compression Ratio (CR)

The compression ratio is to measure the ability of a compression technique to reduce the image size. The Compression ratio is defined as the ratio of an original image and compressed image.

$$CR=\frac{\text{size of original image in bits}}{\text{size of compressed image in bits}} \qquad (1)\ [5]$$

The greater compression ratio means the better the wavelet function.

b) Relative data redundancy (RDR):

The number of information-carrying units in original and compressed images that represent the same information is called as Relative data redundancy.

$$RDR= 1 - \frac{1}{CR} \qquad (2)\ [4]$$

RDR expressed in percentage will give the saved amount of bits after compression.

c) Peak signal-to-noise ratio (PSNR):

PSNR is the ratio used to measure the compression quality of an image in decibels and is given by

$$PSNR = 10\ log_{10}\left[\frac{R^2}{MSE}\right] \qquad (3)\ [5]$$

$$\text{Where, } MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \qquad (4)\ [5]$$

The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The higher the PSNR, the better the quality of the compressed image.

d) Bits per pixel (BPP):

Bits per pixel denote the number of bits used to represent each pixel of an image which has the relation with compression ratio (CR) and is given as,

$$BPP = \frac{8}{CR} \qquad (5)\ [6]$$

The more the bits, more the depth of intensity and more the memory required to store the image.

C. Software tool used to implement Haar wavelet transform

The software used to implement Haar wavelet transform is MATLAB R2015a. The tool box used is Image Processing Tool Box.

III. AN EXAMPLE FOR HAAR WAVELET TRANSFORM

Let matrix A of size 8x8 represent an image of size 8X8

$$A=\begin{bmatrix} 25 & 66 & 90 & 54 & 105 & 50 & 150 & 44 \\ 35 & 140 & 250 & 220 & 190 & 120 & 188 & 75 \\ 92 & 57 & 99 & 177 & 149 & 182 & 77 & 92 \\ 105 & 78 & 100 & 190 & 155 & 170 & 90 & 100 \\ 119 & 90 & 70 & 201 & 177 & 182 & 60 & 120 \\ 95 & 75 & 103 & 210 & 177 & 199 & 100 & 127 \\ 75 & 105 & 99 & 202 & 200 & 254 & 188 & 157 \\ 92 & 109 & 115 & 125 & 215 & 216 & 205 & 210 \end{bmatrix}$$

Let r1 denote first row of the matrix A, i.e.,

r1 = [25 66 90 54 105 50 150 44]

The computation is done 3 times for 2^3 X 2^3 (i.e., 8X8) matrix and the procedure is as follows:

Step 1: Group all the columns of r1 into pairs, i.e.,

[25 66], [90 54], [105 50], [150 44]

Find average of each pair and replace these averages with first half of the row r1.

r1 = [46 72 78 97 105 50 150 44]

Step 2: Find the difference between first element of each group with the corresponding average value and replace this differences with second half of the row r1.

r1 = [46 72 78 97 -21 18 28 53]

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Step 3: Now consider only first half of the row r1 and group these four values into 2 pairs, i.e.,

[46 72], [78 97]

Once again find averages of each pair and replace the averages with first quarter of the row r1.

r1 = [59 88 78 97 -21 18 28 53]

Step 4: Find the difference between first element of each group in r1 with the corresponding average value and replace this differences with second quarter of the row r1.

r1 = [59 88 -13 -10 -21 18 28 53]

Step 5: Now consider only first two elements of the row r1 and group these elements into a single pair, i.e.,

[59, 88]

Once again find average of the pair and replace this average value with first column of row r1.

r1 = [74 88 -13 -10 -21 18 28 53]

Step 6: Find the difference between first element of the group with the corresponding average value and replace this difference value with second column of the row r1.

r1 = [74 -15 -13 -10 -21 18 28 53]

Step 7: The procedure from Step 1 to Step 6 is repeated for all the remaining rows of the matrix A.

Step 8: Now consider row-wise computed matrix for column-wise computation. For the column-wise computation the procedure given in Step 1 to Step 7 is repeated for columns instead of rows. The resulting compressed matrix Z using Haar wavelet transform is

After reconstruction/decompression, the input matrix A is obtained by following the procedure given in section II for reconstruction. The resulting reconstructed matrix Ar is

$$Z = \begin{bmatrix} 133 & -18 & -31 & 25 & -5 & -29 & -1 & 8 \\ -15 & 12 & -7 & -5 & -6 & 16 & 11 & 16 \\ -4 & 3 & -7 & -19 & -27 & 30 & 23 & 31 \\ -15 & 18 & -3 & 13 & 13 & -16 & 4 & -15 \\ -40 & -12 & 31 & -11 & 16 & 2 & -4 & -2 \\ -4 & -3 & -3 & 4 & 2 & 3 & -5 & -2 \\ -4 & 4 & 10 & 4 & 3 & -6 & 4 & -8 \\ -1 & 6 & -11 & 12 & -3 & -24 & -13 & 10 \end{bmatrix}$$

$$Ar = \begin{bmatrix} 23 & 67 & 92 & 54 & 108 & 50 & 152 & 46 \\ 33 & 141 & 254 & 224 & 194 & 120 & 190 & 76 \\ 90 & 54 & 100 & 180 & 155 & 191 & 78 & 96 \\ 106 & 78 & 102 & 194 & 159 & 175 & 92 & 102 \\ 121 & 87 & 71 & 205 & 180 & 188 & 59 & 121 \\ 95 & 73 & 103 & 213 & 180 & 204 & 99 & 129 \\ 73 & 103 & 99 & 205 & 204 & 262 & 192 & 158 \\ 91 & 109 & 115 & 125 & 220 & 226 & 210 & 210 \end{bmatrix}$$

It can be observed that the input matrix A and the reconstructed matrix Ar is almost similar.

IV. RESULTS

Using the implemented algorithm, compression level from level 1 to 9 is possible. But for the correct identification of object of interest in the image is only possible in level 1 to level 4. The original image to be compressed is shown in figure 1. The compressed and reconstructed images of levels 1, 2, 3 and 4 are shown in figure 2 and figure 3 respectively. As the level of compression is increased from level 1 to level 4, smallest discernible details in the corresponding reconstructed images are reduced which in turn will reduce the memory bytes required to store and/or transmission bandwidth required to transmit. Depending upon the application and desirable resolution, level of compression can be chosen.

Fig 1: Original image to be compressed

(a) (b) (c) (d)

Fig. 2: Compressed image using haar wavelet transforms (a) Level 1 compressed image (b) Level 2 compressed image (c) Level 3 compressed image (d) Level 4 compressed image

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(a) (b) (c) (d)

Fig. 3: Reconstructed image using haar wavelet transform (a) Level 1 decompressed image (b)Level 2 decompressed image (c) Level 3 decompressed image (d) Level 4 decompressed image

Table 1 shows the comparison of different level of compression with respect to quality measurement parameters such as PSNR, CR, BPP and RDR.

TABLE I COMPARISON BETWEEN DIFFERENT LEVELS OF COMPRESSION

Sl No.	Level of compression	PSNR	CR	BPP	RDR
1.	1	30.7307	1.65	4.85	0. 3939
2.	2	30.3429	2.16	3.70	0.537
3.	3	30.2911	2.50	3.2	0.60
4.	4	30.2891	2.71	2.95	0.631

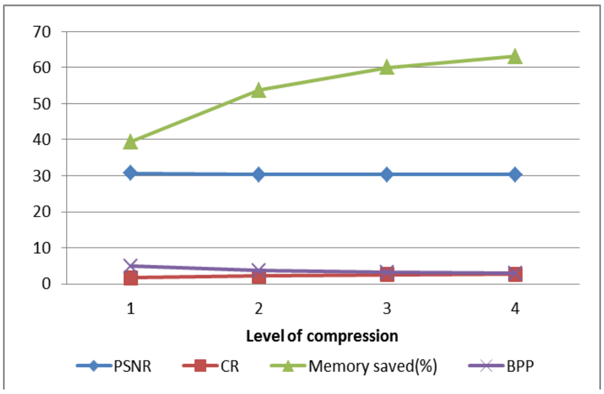

Fig. 4: Graph indicating different parameters to assess the quality of image compression

It has been observe that as levels of compression are increased compression ratio is increased in turn relative data redundancy is also increased (i.e., memory space saved is increased). The minimum and maximum compression ratio that can be achieved for the successful identification of object of interest in the image of size 512X512 is 1.65 and 2.71 respectively and the corresponding memory saved is in the range of 39.39% to 63.1%. The implemented compression method shows the PSNR of 30.7307dB to 30.2891 and BPP has the value of 4.85 to 2.95 for levels 1-4. Figure 4 shows the plot of quality parameters. From the graph plot it can be observed that the PSNR, CR and BPP are almost stable whereas the curve indicating the amount of memory saved is considerably increasing.

V. CONCLUSION

The Haar wavelet transform discussed in this paper is the simplest, efficient and computationally fastest method for image compression. The compressed image can be almost exactly reversible without the edge effects that are a problem with other Wavelet transform methods. The suggested compression method is designed using Matlab software. The synthesis result of the suggested compression method is presented for different levels of compression. Peak SNR, compression ratio, bits per pixel and relative data redundancy of different levels of compression are compared. The discussion and results obtained reflects that the Haar wavelet transform is fast and reliable realization of wavelet transform.

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