A New Image Compression Algorithm using Haar Wavelet Transformation

R.Mehala.
Research Scholar
Department of Computer
Science and Engineering,
Alagappa University, Karaikudi.

K.Kuppusamy, Ph.D
Professor
Department of Computer
Science and Engineering,
Alagappa University, Karaikudi.

ABSTRACT

In this paper, A New Image Compression Algorithm Using Haar Wavelet Transformation is proposed. The proposed 8x8 transform matrix can be obtained by appropriately inserting some 0's and 1/2's in to the Haar Wavelet. The basis of the proposed Haar Wavelet algorithm is based on integers, and made sufficiently sparse orthogonal transform matrix. A Haar Wavelet algorithm for Fast computation is to be developed. Besides, various measures like Compression Ratio, PSNR, Threshold Value and Reconstructed Normalization are calculated. This proposed algorithm has been implemented in Mat Lab.

General Terms

HWT, CR, DWT, PSNR, TV, Sparse Orthogonal.

Keywords

Haar Wavelet Transformation (HWT), Image Compression (IC), Sparse Orthogonal Transform (SOT).

1. INTRODUCTION

Image Transform methods using orthogonal functions are commonly used in image compression.. One of the most widely known image transform method is Discrete Wavelet transform (DWT), used in Image compression standard [2]. The design of an imaging system should begin with an analysis of the physical characteristics of the originals and the means through which the images may be generated. The basic objective of image compression is to find an image representation in which pixels are less correlated.

An Orthogonal Sparse Transform Matrix Based on Image Compression [1] was explained by it is particularly at lower bit rate applications. The transform matrix is made sufficiently sparse by appropriately inserting additional zeros into the matrix proposed by Bouguezel. The algorithm for fast computation is also developed.

The number of Lossy Wavelet coding Algorithms [3] Based on Image Compression has several advantages over DCT based methods at the cost of computational complexity. Fast Haar wavelet for signal processing Based on Computational Complexity [4] has presented a novel Fast Haar wavelet estimator, for application to biosignals such as noninvasive doppler signals and medical images. The signals and images are decomposed and reconstructed by Haar wavelet transform without convolution. Computational time and computational complexity is reduced in Fast Haar wavelet transform.

Image processing and analysis based on the continuous or discrete image transforms [6] has presented a Image processing and analysis based on the continuous or discrete image transforms are classic techniques. The image transforms are widely used in image filtering, data description, etc. Nowadays the wavelet theorems make up very popular methods of image processing, denoising and compression. Considering that the Haar functions are the simplest wavelets, these forms are used in many methods of discrete image transforms and processing.

In this paper we presented A New Image Compression Algorithm using Haar Wavelet Transformation. The orthogonal transform matrix is sparse and has 24 zeros entries. The application of the matrix to grayscale image compression is discussed. A fast algorithm for computation of the matrix is also presented.

2. HAARWAVELETTRANSFORMATION

The family of *N* Haar functions $h_k(t)$ are defined on the interval $0 \le t \le 1$. The shape of the Haar function, of an index *k*, is determined by two parameters: *p* and *q*, where

$$k = 2^p + q - 1$$

and k is in a range of $k = 0, 1, 2, \cdots, N - 1$.

When $k = 0$, the Haar function is defined as a constant $h_0(t) = 1/\sqrt{N}$; when $k > 0$, the Haar function is defined as

$$h_k(t) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \le t < (q-0.5)/2^p \\ -2^{p/2} & (q-0.5)/2^p \le t < q/2^p \\ 0 & \text{otherwise} \end{cases}$$

From the above equation, one can see that *p* determines the amplitude and width of the non-zero part of the function, while *q* determines the position of the non-zero part of the Haar function . The discrete Haar functions formed the basis of the Haar matrix **H**

$$\mathbf{H}_{2N} = \begin{bmatrix} \mathbf{H}_N \otimes [1,1] \\ \mathbf{I}_N \otimes [1,-1] \end{bmatrix}$$

$$\mathbf{H}(0) = 1$$

where

$$\mathbf{I}_N = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$$

and $\otimes$ is the Kronecker product.

The Kronecker product of $\boldsymbol{A} \otimes \boldsymbol{B}$, where $\boldsymbol{A}$ is an $\mathrm{m} \times \mathrm{n}$ matrix and $\boldsymbol{B}$ is a $\mathrm{p} \times \mathrm{q}$ matrix, is expressed as

$$\boldsymbol{A} \otimes \boldsymbol{B} = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix}$$

When $\mathrm{N} = 2^k$

$$\mathbf{H}_\mathrm{N} = \begin{bmatrix} \phi \\ \mathrm{h}_{0,0} \\ \mathrm{h}_{1,0} \\ \mathrm{h}_{1,1} \\ \vdots \\ \mathrm{h}_{k-1,0} \\ \mathrm{h}_{k-1,1} \\ \vdots \\ \mathrm{h}_{k-1,2^{k-1}-1} \end{bmatrix}$$

where $\phi = [1 \quad 1 \quad 1 \quad \cdots \quad 1]$ is a $1 \times \mathrm{N}$ matrix, and $\mathrm{h}_{\mathrm{p,q}}[\mathrm{n}]$ is a Haar function.

The Haar matrix is real and orthogonal, i.e.,

- $\mathbf{H} = \mathbf{H}^*$
- $\mathbf{H}^{-1} = \mathbf{H}^T$, i.e., $\mathbf{H}^T\mathbf{H} = \mathbf{I}$

An un-normalized 8-point Haar matrix $\mathbf{H}_8$ is shown below **Error! Reference source not found.**

$$\mathbf{H}[m,n] = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ 1 & 1 & -1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

From the definition of the Haar matrix **H**, one can observe that, unlike the Fourier transform, **H** matrix has only real element (i.e., 1, -1 or 0) and is non-symmetric.

The first row of **H** matrix measures the average value, and the second row **H** matrix measures a low frequency component of the input vector. The next two rows are sensitive to the first and second half of the input vector respectively, which corresponds to moderate frequency components. The remaining four rows are sensitive to the four section of the input vector, which corresponds to high frequency components. The Haar function with narrower width is responsible for analysing the higher frequency content of the input signal. The inverse 2^k-point Haar matrix is described as $\mathbf{H}^{-1} = \mathbf{H}^\mathrm{T}\mathbf{D}$

$$\mathbf{D}[m,n] = 0 \quad if\ m \neq n$$

$$\mathbf{D}[0,0] = 2^{-k}$$

$$\mathbf{D}[1,1] = 2^{-k}$$

$$\mathbf{D}[\mathrm{n,n}] = 2^{-k+p} \quad if\ 2^p < n < 2^{p+1}$$

For $\mathrm{k} = 3$, un-normalised inverse 8-points Haar transform.

$$\mathbf{D} = \begin{bmatrix} 1/8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/2 \end{bmatrix}$$

3. PROPOSED ORTHOGONAL TRANSFORMMATRIX ALGORITHM

The Haar Algorithm:

- Read the input image into an M by N matrix
- Use the Average and Differencing process.
- Apply the Transformation steps.
- Rows the results.
- Columns the results.
- The Quantization Process.
- The Encoding steps
- Appling the inverse process.

The Haar transform of an array of *n* samples:

1. Treat the array as *n/2* pairs called *(a, b)*
2. Calculate *(a + b) / sqrt(2)* for each pair, these values will be the first half of the output array.
3. Calculate *(a - b) / sqrt(2)* for each pair, these values will be the second half.
4. Repeat the process on the first half of the array.(the array length should be a power of two).

The proposed sparse orthogonal transform matrix can be obtained by appropriately inserting some 0‟s and 1/2 ‟s into the HWT.

$$W1=\begin{pmatrix} \frac{1}{2} & 0 & 0 & 0 & \frac{1}{2} & 0 & 0 & 0 \\ \frac{1}{2} & 0 & 0 & 0 & -\frac{1}{2} & 0 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 & 0 & \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 & 0 & -\frac{1}{2} & 0 & 0 \\ 0 & 0 & \frac{1}{2} & 0 & 0 & 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{2} & 0 & 0 & 0 & -\frac{1}{2} & 0 \\ 0 & 0 & 0 & \frac{1}{2} & 0 & 0 & 0 & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & 0 & 0 & -\frac{1}{2} \end{pmatrix}$$

The first four Coefficients of approximation Coefficient and the last four entries are called the detail Coefficients.

For Next Step,

It is look at the first four entries of as two pairs that it will take their averages.

The third and the fourth entries are obtained by subtracting these averages from the first element of each pair.

Here ,

The Vector can be obtained for multiplying right by the Matrix.

$$W2=\begin{pmatrix} \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & -\frac{1}{2} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & -\frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

For the last step, Average the first two entries and before Subtract the answer from the first entry.

Before it can be obtained for multiplying on the right by the Matrix.

$$W3=\begin{pmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Let,

$$W=W1W2W3=\begin{pmatrix} 1/8 & -1/8 & 1/4 & 0 & 1/2 & 0 & 0 & 0 \\ 1/8 & 1/8 & 1/4 & 0 & -1/2 & 0 & 0 & 0 \\ 1/8 & 1/8 & -1/4 & 0 & 0 & 0 & 1/2 & 0 \\ 1/8 & 1/8 & -1/4 & 0 & 0 & 0 & 1/2 & 0 \\ 1/8 & -1/8 & 0 & 1/4 & 0 & 0 & 1/2 & 0 \\ 1/8 & -1/8 & 0 & 1/4 & 0 & 0 & -1/2 & 0 \\ 1/8 & -1/8 & 0 & -1/4 & 0 & 0 & 0 & 1/2 \\ 1/8 & -1/8 & 0 & -1/4 & 0 & 0 & 0 & -1/2 \end{pmatrix}$$

The Columns of the Matrix W1 from an orthogonal subset of Columns. W1 is invertible. The same is true for W2 and W3. As a product of invertible Matrices , W is also invertible and its Columns from an orthogonal basis of Vector. The inverse of W is given by:

$$W^{-1}=W_3^{-1}\,W_2^{-1}\,W_1^{-1}.$$

The fact the W is invertible allows us to retrieve our image from the compressed from using the relation.

4. SIMULATION AND RESULTS

The proposed technique is demonstrated through computer simulation running on Microsoft Window XP, Intel Core2 Duo CPU, 3 GHz Platform. Peak signal to noise ratio (PSNR) and Compression Ratio(CR).

$$C_R=\frac{\text{Uncompressed Image Size}}{\text{Compressed Image Size}}=\frac{\text{Usize}}{\text{Csize}}$$

U Size =M X N X K

C Size= Size of Compressed Image file Stored in a Disk.

The experimental inputs for the proposed method are Cameraman .jpg and aeroplane.bmp images respectively. The CR is 84.55 , 84.27 and the PSNR is 99.74 and 99.17.The sparse of the proposed matrix seems to be seriously affecting compression performance for higher bit rates (lower compression) on both the images but the image quality is high. The proposed matrix is applicable to low power and portable devices such as PDAs, digital camera and mobile phones, where conventional DCT transform or wavelet coding algorithms are not suitable.

Table 1. Performance factors calculation

Image Name	**Decomp. Level**	**Original Size**	**Compressed .Img**	**Comp.Ratio**	**PSNR**
Cameraman.jpg	2	32.9 KB	1.13KB	84.55	99.74
Lena.jpg	2	49.7 KB	1.83KB	84.33	99.00
Wpeppers.jpg	2	256 KB	4.44KB	84.56	99.95
Mehala.jpg	2	12.5 KB	470Bytes	84.60	99.91
Aeroplane.bmp	2	7.31 KB	404Bytes	84.27	99.17

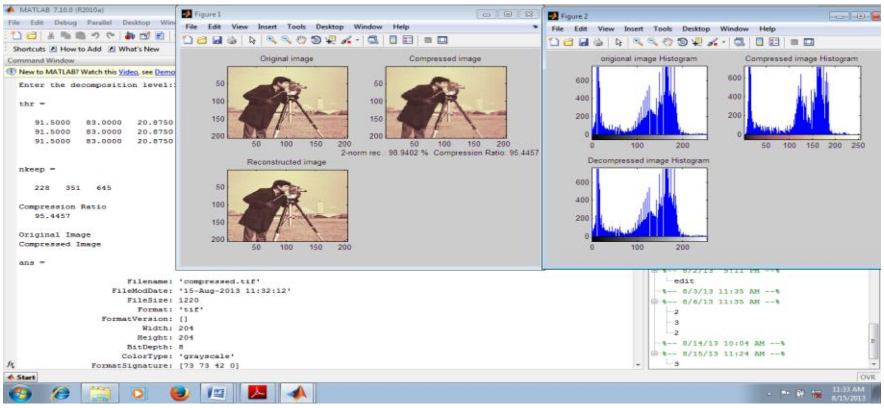

Fig 1: Image Compression of Cameraman.jpg

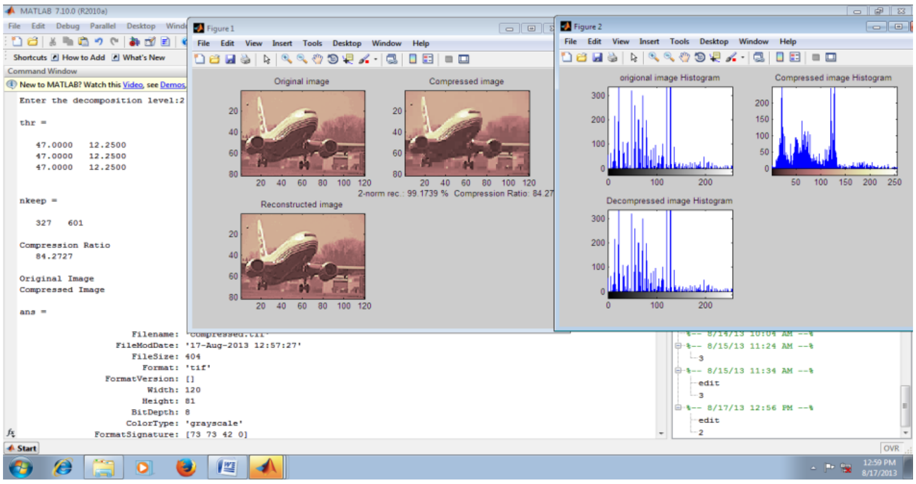

Fig 2: Image Compression of Aeroplane.bmp

5. CONCLUSION

In this paper, An image compression technique using Haar Wavelet Transformation. In these cases, the importance of the compression of image is greatly felt. A low complex 2D image compression method using Haar wavelets as the basis functions along with the quality measurement of the compressed images have been presented here.

As for the further work, the tradeoff between the value of the threshold ε and the image quality can be studied and also fixing the correct threshold value is also of great interest. It is more thorough the comparison of various still image quality measurements, algorithms may be conducted. Though many published algorithms left a few parameters unspecified, here good estimates of them for implementation have been provided.

6. REFERENCES

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