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The Modified 2D-Haar Wavelet Transformation in Image Compression

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Abstract: This paper proposes a modified simple but efficient calculation schema for 2D-Haar wavelet transformation in image compression. The proposed work is aimed at developing computationally efficient and effective algorithms for lossy image compression using wavelet techniques. The work is particularly targeted towards wavelet image compression using Haar Transformation with an idea to minimize the computational requirements by applying different compression thresholds for the wavelet coefficients and these results are obtained in fraction of seconds and thus to improve the quality of the reconstructed image. The promising results obtained concerning reconstructed images quality as well as preservation of significant image details, while, on the other hand achieving high compression rates and better image quality. It also exploits the correlation characteristics of the wavelet coefficients as well as second order characteristics of images in the design of improved lossy compression systems for medical and noisy images.

Key words: Haar wavelet transform · lossy compression technique · threshold

I. INTRODUCTION

Image compression is a fast paced and dynamically changing field with many different varieties of compression methods available. Images contain large amount of data hidden in them, which is highly correlated. A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information [1].

Research advances in wavelet theory have created a surge of interest in applications like image compression. The investigation and design of computationally efficient and effective software algorithms for lossy image compression forms the primary objective of this thesis. In wavelet image compression, parts of an image is described with reference to other parts of the same image and by doing so, the redundancy of piecewise self-similarity is exploited. There are a number of problems to be solved in image compression to make the process viable and more efficient. A lot of work has been done in the area of wavelet based lossy image compression. However, very little work has been done in lossless image compression using wavelets to improve image quality [2]. So the proposed methodology of this paper is to achieve high compression ratio in images using 2D-Haar Wavelet Transform by applying different compression thresholds for the wavelet coefficients. That is, different compression ratios are applied to the wavelet coefficients belonging in the different regions of interest, in which either each wavelet domain band of the transformed image. Regarding the first method, its reconstruction process involves using the inverse HWT on the remaining wavelet coefficients. Concerning the second method, its reconstruction process involves linear combination of the reconstructed regions of interest. An experimental study is conducted to qualitatively assessing both approaches in comparison with the original HWT compression technique, when applied to a set of images.

II. Properties and advantages of haar wavelet transform:

The Properties of the Haar Transform are described as follows:

i) Haar Transform is real and orthogonal. Therefore

$$Hr = Hr^* \tag{1}$$

$$Hr^{-1} = Hr^{T} \tag{2}$$

Haar Transform is a very fast transform.

ii) The basis vectors of the Haar matrix are sequency ordered.

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iii) Haar Transform has poor energy compaction for images.
iv) Orthogonality: The original signal is split into a low and a high frequency part and filters enabling the splitting without duplicating information are said to be orthogonal.
v) Linear Phase: To obtain linear phase, symmetric filters would have to be used.
vi) Compact support: The magnitude response of the filter should be exactly zero outside the frequency range covered by the transform. If this property is satisfied, the transform is energy invariant.
vii) Perfect reconstruction: If the input signal is transformed and inversely transformed using a set of weighted basis functions and the reproduced sample values are identical to those of the input signal, the transform is said to have the perfect reconstruction property. If, in addition no information redundancy is present in the sampled signal, the wavelet transform is, as stated above, ortho normal [3].

The advantages of Haar Wavelet transform as follows:

1. Best performance in terms of computation time.
2. Computation speed is high.
3. Simplicity
4. HWT is efficient compression method.
5. It is memory efficient, since it can be calculated inplace without a temporary array.

III.Procedure for Haar Wavelet Transform: To calculate the Haar transform of an array of *n* samples:

1. Find the average of each pair of samples. ($n/2$ averages)
2. Find the difference between each average and the samples it was calculated from. ($n/2$ differences)
3. Fill the first half of the array with averages.
4. Fill the second half of the array with differences.
5. Repeat the process on the first half of the array. (The array length should be a power of two)

IV. IMPLEMENTATION METHODOLOGY

Each image is presented mathematically by a matrix of numbers. Haar wavelet uses a method for manipulating the matrices called averaging and differencing. Entire row of a image matrix is taken, then do the averaging and differencing process. After we treated entire each row of an image matrix, then do the averaging and differencing process for the entire each column of the image matrix. Then consider this matrix is known an semifinal matrix (T) w hose rows and columns have been treated. This procedure is called wavelet transform. Then compare the original matrix and last matrix that is semifinal matrix (T), the data has became smaller. Since the data has become smaller, it is easy to transform and store the information. The important one is that the treated information is reversible. To explain the reversing process we need linear algebra. Using linear algebra is to maximize compression while maintaining a suitable level of detail.

A. Wavelet Compression Methodology: From Semi final Matrix (T) is ready to be compressed. Definition of Wavelet Compression is fix a non negative threshold value ε and decree that any detail coefficient in the wavelet transformed data whose magnitude is less than or equal to zero (this leads to a relatively sparse matrix). Then rebuild an approximation of the original data using this doctored version of the wavelet transformed data. In the case of image data, we can throw out a sizable proportion of the detail coefficients in this and obtain visually acceptable results [4, 5, 8]. This process is called lossless compression. When no information is loss (e.g., if $\epsilon = 0$). Otherwise it is referred to as lossy compression (in which case $\epsilon>0$). In the former case, we can get our original data back and in the latter we can build an approximation of it. We have lost some of the detail in the image but it is so minimal that the loss would not be noticeable in most cases.

B. Linear Algebra Methodology: To apply the averaging and differencing using linear algebra [6]. We can use matrices such as A1, A2, A3….. An. that perform each of the steps of the averaging and differencing process.

i. When multiplying the string by the first matrix of the first half of columns are taking the average of each pair and the last half of columns take the corresponding differences.
ii. The second matrix works in much the same way, the first half of columns now perform the averaging and differencing to the remaining pairs and the identity matrix in the last half of columns carry down the detail coefficient from step i.
iii. Similarly in the final step, the averaging and differencing is done by the first two columns of the matrix and the identity matrix carries down the detail coefficient from previous step.

iv. To simplify this process, we can multiply these matrices together to obtain a single transform matrix W=A1A2A3) we can now multiply our original string by just one transform matrix to go directly form the original string to the final results of step iii.
v. In the following equation we simplify this process of matrix multiplication. First the averaging and differencing and second the inverse of those operation.

$$1.T= ((AW)^{T} W))^{T}$$
$$T= (W^{T} A^{T} W)^{T}$$
$$T= W^{T} (A^{T})^{T} (W^{T})^{T}$$
$$T=W^{T}AW \tag{3}$$

$$2.(W^{1})^{-1} T W^{-1} = A$$
$$(W^{-1})^{1}TW^{-1}=A \tag{4}$$

V.proposed algorithm:

1. Read the image from the user.
2. Apply 2 D DWT using haar wavelet over the image
3. For the computation of haar wavelet transform, set the threshold value 25, 10, 5 and 1% ie., set all the coefficients to zero except for the largest in magnitude 25, 10, 5 and 1%. And reconstruct an approximation to the original image by apply the corresponding inverse transform with only modified approximation coefficients.
4. This simulates the process of compressing by factors of ¼, 1/10, 1/20, 1/100 respectively.
5. Display the resulting images and comment on the quality of the images.
6. Calculate MSE, MAE and PSNR values of different Compression Ratios for corresponding Reconstructed images.
7. Then add a small amount of white noise to the input image. Default: variance = 0.01, sigma = 0.1, mean = 0
8. To compute the haar wavelet transform, set all the approximation coefficients to zero except those whose magnitude is larger than 3 sigma.
9. This same case is applicable to detail coefficients that is horizontal, vertical & diagonal coefficients.
10. Reconstruct an estimate of the original image by applying the corresponding inverse transform.
11. Display and compare the results by computing the root mean square error, PSNR and mean absolute error of the noisy image and the denoising image.
12. The same process is repeated for various images and compare its performance.

Alternative approach (Reconstruction) Algorithm is described as follows:

1. Read the image cameraman.tif from the user.
2. Using 2D wavelet decomposition with respect to a haar wavelet computes the approximation coefficients matrix CA and detail coefficient matrixes CH, CV, CD (horizontal, vertical & diagonal respectively) which is obtained by wavelet decomposition of the input matrix ie., im_input.
3. From this, again using 2D wavelet decomposition with respect to a haar wavelet computes the approximation and detail coefficients which are obtained by wavelet decomposition of the CA matrix. This is considered as level 2.
4. Again apply the haar wavelet transform from CA matrix which is considered as CA1 for level 3.
5. Do the same process and considered as CA2 for level 4
6. Take inverse transform for level 1, level 2, level 3 & level 4 that ie., im_input, CA, CA1, CA2.
7. Reconstruct the images for level 1, level 2, level 3 & level 4.
8. Display the results of reconstruction 1, reconstruction 2, reconstruction 3, reconstruction 4 ie., level 1, 2, 3, 4 with respect to the original image.

VI. RESULTS AND DISCUSSIONS

The project deals with the implementation of the haar wavelet compression techniques and a comparison over various input images. We first look in to results of wavelet compression technique by calculating their comparison ratios and then compare their results based on the error metrics which is shown in Table 1.

VII. Effects on Compression Ratio Vs Various Parameters: In our experiments, we used the gray scale sample, cameraman.tif of size 256*256. And measured the compression ratio and the PSNR of the compressed image.The quality of compressed image depends on the no of decompositions. The no of decompositions determines the resolution of the lowest level in wavelet domain. Using larger no of decompositions, that will be more successful in resolving important HWT coefficients from less important coefficients [7, 9,10]. After decomposing the image and representing it with wavelet coefficients, compression can be performed by ignoring all coefficients below some threshold. In this experiment, compression is obtained by wavelet coefficient threshold.

(a) (b) (c)

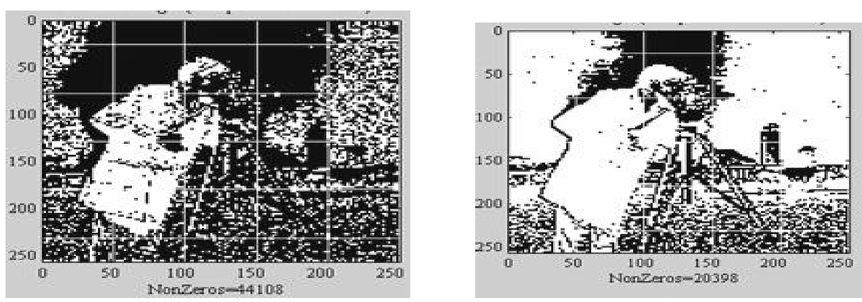
a) Original image, b) Reconstructed image N=1, c) Reconstructed image N=2

Fig. 1: Original and reconstructed images for level 1 and level2

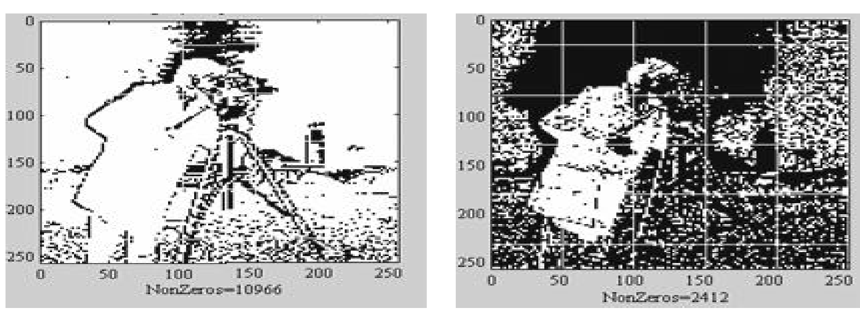
(a) (b) (c)

a) Original image, b) Noisy image: Mean = 0.0, Variance = 0.01, Sigma = 0.1,
c) Denoising image: Threshold = 3* Sigma

Fig. 2: Original, noisy (Gaussian) and denoising images



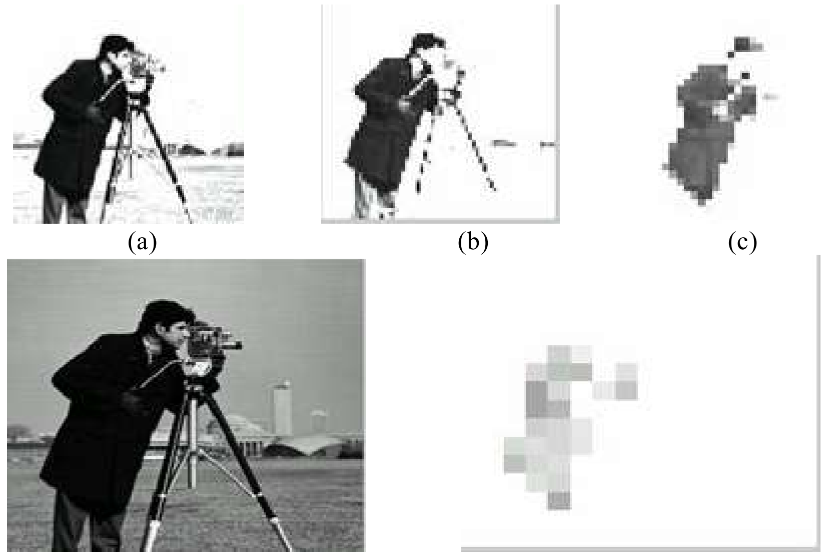
(a) (b)



(c) (d)

a) Compression ratio 4:1, b) Compression ratio 10:1
c) Compression ratio 20:1, d) Compression ratio 100:1

Fig. 3: Compressed images with haar wavelet transform for different compression ratios



(a) (b) (c)

(d) (e)

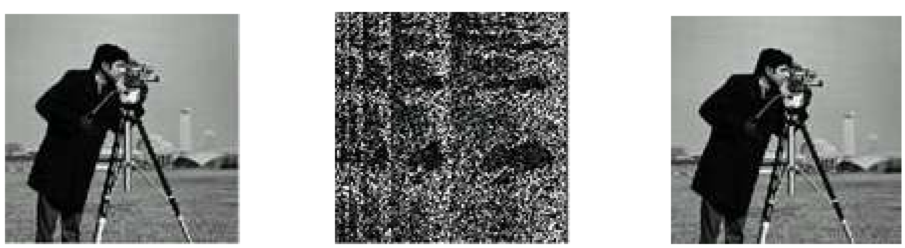
a) Level 1, b) Level 2, c) Level 3, d) Original image, e) Level 4

Fig. 4: Original and haar wavelet transformed images for different levels

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

a) Level 1, b) Level 2, c) Level 3, d) Level 4

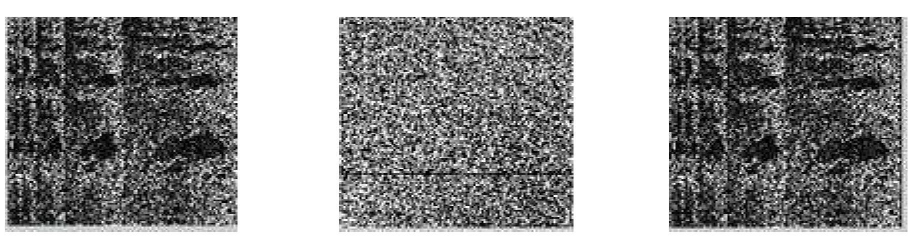
Fig. 5: Reconstructed Images for different Levels



(a) (b) (c)

a) Original image, b) Decomposed image, c) Reconstructed image

Fig. 6: Original, decomposed and reconstructed images with first haar transformation



(a) (b) (c)

a) Original image, b) Decomposed image, c) Reconstructed image

Fig. 7: Original, decomposed and reconstructed images with second haar transformation

Table 1: Different types of error metrics with respect to various compression ratios

	Error metrics		
Compression ratios	MSE	RMSE	PSNR
4:01	9937.92	99.6891	18.7841
10:01	14380.1	119.917	15.0893
20:01	15990.1	126.452	14.028
100:1	17453.3	132.111	13.1524

Table 2: Calculation of different kinds of error metrics with respect to various input images under compression ratio 100:1

SI.No	Image	No of elements to store in bytes	MSE	PSNR
1	cman.tif	256*256	17543.3	13.1524
2	Rice.tif	256*256	13094.7	16.0257
3	Mri.tif	128*128	1248.83	39.5257
4	Eight.tif	242*308	41227.2	4.5567
5	Bonemarr.tif	238*270	28009.8	8.4222

The quality of the reconstructed image is measured using the error metrics:

i) MSE
ii) PSNR

The values of MSE and PSNR are calculated for all test images and are provided in Table 2.

VIII. CONCLUSION

This paper reported is aimed at developing computationally efficient and effective algorithm for lossy image compression using wavelet techniques. So this proposed algorithm developed to compress the image so fastly. The promising results obtained concerning reconstructed image quality as well as preservation of significant image details, while on the other hand achieving high compression rates. Results shows that reduction in encoding time with little degradation in image quality compared to existing methods. While comparing the developed method with other methods compression ratio is also increased.

Some of the applications require a fast image compression technique but most of the existing technique requires considerable time. So this proposed algorithm developed to compress the image so fastly. The main bottleneck in the compression lies in the search of domain, which is inherently time expensive. This leads to excessive compression time. The main bottleneck in the compression lies in the search of domain, which is inherently time expensive. This leads to excessive compression time. Image denoising method using wavelet for noisy image could be developed. This yield better result in image compression techniques using wavelet for noisy input image

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