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IMAGE COMPRESSION USING HAAR WAVELET TRANSFORM

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Abstract*:* This paper proposes a simple but efficient calculation scheme 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.

Keywords: Image Compression, Haar Transform, wavelet transform

I. INTRODUCTION

Image files have become one of the most common file types to be used and shared today. But along with their convenience, image files are often large, making them difficult to store and transmit.

While image compression involves the removal of image data, it does not pose a risk to an image's overall quality. Overall, image compression is necessary in any instance where images need to be stored, transmitted or viewed quickly and efficiently. When the basics of image compression are understood, the benefits become much more apparent. Here the low complex 2D image compression method using wavelet as a basis function and approach to measure the quality of the compressed image is presented.

II. WAVELET TRANSFORM

Wavelet theory had been developed independently on several fronts. Different signal processing techniques, developed for signal and image processing applications, had significant contribution in this development. Some of the major contributors to this theory are: multiresolution signal processing used in computer vision; sub band coding, developed for speech and image compression; and wavelet series expansion, developed in applied mathematics. The wavelet transform is successfully applied to nonstationary signals and images. Some of the application areas are: nonlinear filtering or denoising, signal and image compression, speech coding, seismic and geological signal processing, medical and biomedical signal and image processing, and communication.

Wavelet theory is based on analyzing signals to their components by using a set of basis functions. One important characteristic of the wavelet basis functions is that they relate to each other by simple scaling and translation. The original wavelet function, known as mother wavelet, which is generally designed based on some desired characteristics associated to that function, is used to generate all basis functions. For the purpose of multiresolution formulation, there is also a need for a second function, known as scaling function, to allow analysis of the function to finite number of components. These functions and their interrelations will be discussed further in the following sections.

In most wavelet transform applications, it is required that the original signal be synthesized from the wavelet coefficients. This condition is referred to as perfect reconstruction. In some cases, however, like pattern recognition type of applications, this requirement can be relaxed. In the case of perfect reconstruction, in order to use same set of wavelets for both analysis and synthesis, and compactly represent the signal, the wavelets should also satisfy orthogonality condition. By choosing two different sets of wavelets, one for analysis and the other for synthesis, the two sets should satisfy the biorthogonality condition to achieve perfect reconstruction.

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In general, the goal of most modern wavelet research is to create a mother wavelet function that will give an informative, efficient, and useful description of the signal of interest. It is not easy to design a uniform procedure for developing the best mother wavelet or wavelet transform for a given class of signals. However, based on several general characteristics of the wavelet functions, it is possible to determine which wavelet is more suitable for a given application

III. HAAR WAVELET TRANSFORM

Alfred Haar (1885-1933) was a Hungarian mathematician who worked in analysis studying orthogonal systems of functions, partial differential equations, Chebyshev approximations and linear inequalities. In 1909 Haar introduced the Haar wavelet theory. A Haar wavelet is the simplest type of wavelet . In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform..

The mathematical prerequesites will be kept to a minimum; indeed, the main concepts can be understood in terms of addition, subtraction and division by two. We also present a linear algebra implementation of the Haar wavelet transform, and mention important recent generalizations. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two subsignals of half its length. The Haar wavelet transform has a number of advantages:

- It is conceptually simple and fast
- It is memory efficient, since it can be calculated in place without a temporary array.
- It is exactly reversible without the edge effects that are a problem with other wavelet transforms.
- It provides high compression ratio and high PSNR (Peak signal to noise ratio).
- It increases detail in a recursive manner.

The Haar
Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation.

Data compression in multimedia applications has become more vital lately where compression methods are being rapidly developed to compress large data files such as images. Efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size.

Recently the use of Wavelet Transforms and Discrete Cosine Transform (DCT) for image compression was investigated [1]. The usability and efficiency of these methods depend on the application areas that require either high transmission rate or high quality decompression. Lossless compression algorithm provides a compression which, when decompressed the exact original data can be obtained. This is the case when binary data such as executables and documents are compressed. On the other hand, images might not be reproduced 'exactly', but an approximation of the original image is enough for most purposes as long as the error between the original and the compressed image is tolerable. The general purpose of compression systems is to compress images, but the result is less than optimal.

Although the use of Wavelet Transforms was shown to be more superior to DCT when applied to image compression, some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space. This also means that lossy compression techniques such as DCT can be used in this area. Image compression using DCT is a simple compression method that was first applied in 1974 [2]. It is a popular transform used for some of the image compression standards in lossy compression methods. The disadvantage of using DCT image compression is the high loss of quality in compressed images, which is more notable at higher compression ratios. Recent work on finding optimum compression suggested criteria that was based on visual inspection and computed analysis of the reconstructed images [1].

Visual inspection and observation by humans is an empirical analysis that involves a number of people who observe the smoothness and edge continuity of certain objects within reconstructed images and then decide which compression ratio provides a compromise between high compression ratio and minimal loss of quality [1],[2].

The aim of this paper is to give brief introduction to the subject by showing how the Haar wavelet transform allows information to be encoded according to \levels of detail." In one sense, this parallels the way in which we often process information in our everyday lives. Our investigations enable us to give two interesting applications of wavelet methods to digital images: compression and progressive transmission.

The mathematical prerequesites will be kept to a minimum; indeed, the main concepts can be understood in terms of addition, subtraction and division by two. We also present a linear algebra implementation of the Haar wavelet transform, and mention important recent generalizations.

IV. PERFORMANCE ANALYSIS

System operation

a) Convert the image in the matrix form:

In the computer image is stored in the form of array of pixels. These pixel values are ranging from zero (for black) to some positive number (for white). In order to transform a matrix representing an image using Haar Wavelet

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Transform. We will first discuss the method of transforming vectors called averaging and differencing.
Consider a pixel matrix P representing 8x8 image

P=

576	704	1152	1280	1344	1472	1536	1536
704	640	1156	1088	1344	1408	1536	1600
768	832	1216	1472	1472	1536	1600	1600
832	832	960	1344	1536	1536	1600	1536
832	832	960	1216	1536	1600	1536	1536
960	896	896	1088	1600	1600	1600	1536
768	768	832	832	1280	1472	1600	1600
448	768	704	640	1280	1408	1600	1600

b) Calculate the row-column transformed matrix (T)
To demonstrate how wavelet transform
works we first describe transforming data string called averaging and differencing. To understand what it actually does we treat each row as separate data string and the final results are:

T=

576	704	1152	1280	1344	1472	1536	1536
640	1216	1408	1536	**-64**	**-64**	**-64**	**0**
928	1472	**-288**	**-64**	**-64**	**-64**	**-64**	**0**
1200	**-272**	**-288**	**-64**	**-64**	**-64**	**-64**	**0**

Since the data string has length 2^3=8, there are three steps in transform process. The first four numbers in the second row are the averages of pairs in first row. Similarly, the first two numbers in the third row are the averages of those four averages taken two at a time and the first entry in the last row is the average of the preceding two computed averages.

The remaining numbers, shown in bold, measure deviations from the various averages. The first from the first elements of the pairs that gave rise to them: subtracting 640, 1216, 140, 1536 from 576, 1152, 1344, 1536,element by element yields 64, 64, 64 and 0. These are called detail coefficients. They are repeated in each subsequent row of the table.The third and fourth entries in the third row are obtained by subtracting the first and second entries in that row from the first elements of the pairs that start row two subtracting 928, 1472 from 640,1408 element by element yields 288, 64.These two new detail coefficients are also repeated in each subsequent row of the table. Finally, the second entry in the last row,272 is the detail coefficient obtained by subtracting the overall average 1200 from the 928 that starts row three.

Averaging and differencing is a reversible process. Here we have lost nothing during transformation. After completing this process on all rows, we move forward in doing the same transformation on columns. The final result is a new 8x8 matrix T, called the Haar wavelet transform of P.

Applying the averaging and differencing technique to P we get the transformed matrix T as follows:

T=

1212	-306	-146	-54	-24	-68	-40	4
30	36	-90	-2	8	-20	8	-4
-50	-10	-20	-24	0	72	-16	-16
82	38	-24	68	48	-64	32	8
8	8	-32	16	-48	-48	-16	16
20	20	56	-16	-16	32	-16	-16
-8	8	-48	0	-16	-16	-16	-16
44	36	0	8	80	-16	-16	0

This matrix has one overall average value in the top left hand corner, and 63 detail elements
The point of the wavelet transform is that regions of little variation in the original data manifest themselves as small or zero elements in the wavelet transformed version. The 0's in T are due to the occurrences of identical adjacent elements in P , and the - 2; -4, and 4 in T can be explained by some of the nearly identical adjacent elements in P . A matrix with a high proportion of zero entries is said to be sparse

V. COMPRESSION

The real pay-off in the wavelet transmission game is not so much the expectation of sparsity of the transformed matrices, it's the fact that we can fiddle with the \mostly detail" versions to make lots of entries zero: we can alter the transformed matrices, taking advantage of \regions of low activity," and then apply the inverse wavelet transform to this doctored version, to obtain an approximation of the original data
Thus we arrive at the door of wavelet compression: Fix a nonnegative threshold value ε and decree that any detail coefficient in the wavelet transformed data whose magnitude is less than or equal to ε will be reset to zero (hopefully, this leads to a relatively sparse matrix), then rebuild an approximation of the original data using this doctored version of the wavelet transformed data. The surprise is that in the case of image data, we can throw out a sizable proportion of the detail coefficients in this way and obtain visually acceptable results. This process is called lossless compression when no information is lost (e.g. if ε =0) otherwise it's referred to as lossy compression
Thresholding:
For lossy image compression, we fix a non negative thresholding value and any detail coefficient wavelet data in the transformed matrix whose value is less than or equal to thresholding value is set to the zero. A matrix with high proportion of zero entries is said to be sparse. In lossy compression the transformed matrix is sparser than original matrix.

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For the instant, we set a thresholding value i.e. ε =20. That means we reset the values in transformed matrix which are less than or equal to 20 to zero. We get the doctored matrix D,

D=

1212	-306	-146	-54	-24	-68	-40	0
30	36	-90	0	0	0	0	0
-50	0	0	-24	0	72	0	0
82	38	-24	68	48	-64	32	0
0	0	-32	0	-48	-48	0	0
0	0	-56	0	0	32	0	0
0	0	-48	0	0	0	0	0
44	36	0	0	80	0	0	0

Applying the inverse wavelet transform to D, we get this reconstructed approximation R

R=

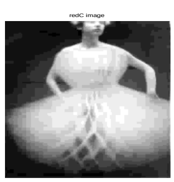
582	726	1146	1234	1344	1424	1540	1540
742	694	1178	1074	1344	1424	1540	1540
706	754	1206	1422	1492	1572	1592	1592
818	866	1030	1374	1492	1572	1592	1592
856	808	956	1220	1574	1590	1554	1554
952	904	860	1124	1574	1590	1554	1554
776	760	826	836	1294	1438	1610	1610
456	760	668	676	1278	1422	1594	1594

VI. RESULTS

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 compression ratios.

Original Image (663KB)

Compressed Image (349KB)



a) Original b) Compressed c)RedC

d)GreenC e)BlueC

Comparison between Haar and DCT for a sample image of 'dancer2'

	Compression Ratio	PSNR
Haar	99.5733 %	-34.59
DCT	50 %	-42.07

From above observations we came to know that compression ratio and PSNR got by haar is more than that of DCT. Greater PSNR gives better picture quality.

VII. 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.

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Biography

Shabanam Tamboli did her Bachelors & Masters degree in electronic engineering from Shivaji University, Kolhapur, Maharaashtra. And registered for Ph.D. degrees at Vishwesharya Technological University, Belgaum, Karnataka in Electronics & Communication engineering. She has total 10 years of teaching experience. She has published more than 10 technical papers in national, international conferences & international journals. Her field of interest is image processing. She is a life member of ISTE.

Dr. V. R. Udupi did his bachelor's degree in Electronics and communication Engineering. from Mysore University in 1984 and pursued his master's degree in Electronics Engineering with computer applications as specialization from Shivaji University, Kolhapur, Maharashtra state, in 1989. He has completed his doctoral degree in Electrical Engineering from Shivaji University, Kolhapur, Maharashtra state, in 2003. His field of interests includes signal processing, Image processing, cryptography, and knowledge based systems. Currently he is working as a professor in Electronic and communication department of Gogte institute of Technology, Belgaum, Karnataka state. He has 28 years of total teaching experience and currently he is guiding 05 research scholars and has guided 04 candidates for Ph.D. He has published more than 42 technical papers in national and international conferences and 08 articles in journals. He is a life member of ISOI, SSI, CSI, BMESI, and ISTE.