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Comparison and Analysis of an efficient Image Compression Technique Based on Discrete 2-D wavelet transforms with Arithmetic Coding

Deepika Sunoriya[1], Uday Pratap Singh[2], Vineet Ricchariya[3]
M.Tech Research Scholar, LNCT Bhopal[1]
Assistant Professor, LNCT Bhopal[2]
Professor and Head Department of Computer Science and Engineering, LNCT Bhopal[3]

Abstract

When a great deal is known about the regularities in the files to be compressed, e.g., in the compression of image, audio, photo and video data, it is possible to match different compression algorithms with different parts of the data in such a way to achieve the maximum compression ratio, thereby providing significant reductions in file sizes. These algorithms are difficult to derive and are often the result of many person years of effort. Nonetheless, these are so successful that effectively some types of data are regularly saved, kept and transferred, only in compressed form, to be decompressed automatically and transparently to the user only when loaded into applications that make use of them. Our proposed approach is the combination of several approaches to make the compression better than the previous used approach. We first apply two Levels Discrete Wavelet Transform and then apply Walsh-Wavelet Transform on each 8x8 block of the low-frequency sub-band, then Split all DC values form each transformed block 8x8. Finally we perform compression by using arithmetic coding. In our algorithm we provide the basis of accepting images from the database. We concentrate the type of the wavelet we use like db1, db2, db3 etc. Then we use the quantization factor which is CF1 and CF2 in our case. We use the value as 0.05 and 0.2 as the quantization factor. After matlab simulation we can find our results suitable than the previous work.

Keywords

Walsh-Wavelet Transform, Image Compression, db1, db2, Quantization

1. Introduction

In imaging science, image processing is any form of signal processing for which the input is an image, instead of signal the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible [1]. Image processing is a rapidly growing area of computer science. Fields which traditionally used analog imaging are now switching to digital systems, for their flexibility and affordability. Important examples are medicine, film and video production, photography, remote sensing, and security monitoring [2]. These and other sources produce huge volumes of digital image data every day, more than could ever be examined manually. Digital image[3][4] processing is concerned primarily with extracting useful information from images. Ideally, this is done by computers, with little or no human intervention. Image processing algorithms may be placed at three levels. At the lowest level are those techniques which deal directly with the raw, possibly noisy pixel values, with denoising and edge detection being good examples. In the middle are algorithms which utilize low level results for further means, such as segmentation and edge linking. At the highest level are those methods which attempt to extract semantic meaning from the information provided by the lower levels.

Images are important documents nowadays; to work with them in some applications they need to be compressed [5], more or less depending on the purpose of the application. There are some algorithms that perform this compression in different ways; some are lossless and keep the same information as the original image, some others loss information when compressing the image. Some of these compression methods are designed for specific kinds of images, so they will not be so good for other kinds of images. Some algorithms even let you change parameters they use to adjust the compression better to the image.

There are different formats works [6][7][8] for each of the images. There are some formats that match some images better than others depending in what you are looking for to obtain, and the type of image you are working with. The image compression techniques are broadly classified into two categories depending whether or not an exact replica of the original image could be reconstructed using the compressed image.

These are:
1. Lossless technique
2. Lossy technique

Lossless compression technique
In lossless compression techniques, the original image can be perfectly recovered from the compressed or encoded image. These are also called noiseless since they do not add noise to the signal (image).It is also known as entropy coding since it use statistics/decomposition techniques to eliminate/minimize redundancy. Lossless compression is used only for a few applications with stringent requirements such as medical imaging.

Lossy compression technique
Lossy schemes provide much higher compression ratios than lossless schemes. Lossy schemes are widely used since the quality of the reconstructed images is adequate for most applications. By this scheme, the decompressed image is not identical to the original image, but reasonably close to it. Major performance considerations of a lossy compression scheme include:

1. Compression ratio
2. Signal - to - noise ratio
3. Speed of encoding & decoding.

We provide here an overview of Image Compression Technique. The rest of this paper is arranged as follows: Section 2 introduces Image Compression Techniques; Section 3 describes about Recent Scenario; Section 4 shows the proposed approach; Section 5 describes Conclusion.

2. Recent Scenario

In 2006, Matthew J. Zukoski et al. [9] as medical/biological imaging facilities move towards complete film-less imaging, compression plays a key role. Although lossy compression techniques yield high compression rates, the medical community has been reluctant to adopt these methods, largely for legal reasons, and has instead relied on lossless compression techniques that yield low compression rates. The true goal is to maximize compression while maintaining clinical relevance and balancing legal risk. They propose a novel model-based compression technique that makes use of clinically relevant regions as defined by radiologists. Lossless compression is used in these clinically relevant regions, and lossy compression is used everywhere else.

In 2007, R.Sukanesh et al. [10] a novel approach of information theory based Minimum Relative Entropy (MRE) and Entropy methods for image compression are discussed. A two stage compression process is performed through homogenous MRE method, and heterogeneous MRE. The compressed images are reconstructed through Region growing techniques. The performance of image compression and restoration is analyzed by the estimation of parametric values such as Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). Higher the PSNR better the reconstruction process. Six radiographic medical images of various sizes are analyzed and Maximum PSNR of 33 is achieved.

In 2008, K. Veeraswamy,et al. [11] an adaptive image compression algorithm is proposed based on the prediction of AC coefficients in Discrete Cosine Transform (DCT) block during reconstruction of image. In the prediction phase, DC values of the nearest neighbor DCT blocks are utilized to predict the AC coefficients of center block. Surrounding DC values of a DCT blocks are adaptively weighed for AC coefficients prediction. Linear programming is used to calculate the weights with respect to the image content. Results show that this method is good in terms of good Peak Signal to Noise Ratio (PSNR) and less blocking artifacts. The proposed scheme has been demonstrated through several experiments including Lena. Reconstructed image is of good quality with same compression ratio compared to the existing technique in the literature. In addition, an image watermarking algorithm is proposed using DCT AC coefficients obtained. The performance of the proposed watermarking scheme is measured in terms of PSNR and Normalized Cross Correlation (NCC). Further, this algorithm is robust for various attacks including JPEG compression on watermarked image.

In 2010, Jianfeng Wanget al. [12] proposed an propose an effective and fast shot cut detection algorithm directly in MPEG compressed domain. The proposed shot cut detection test the different between the current frame and next frame through the extracting the feature of each frame. When extract the features of frame, statistical parameters m1-σ from DWT coefficients without its inverse transform was computed, Except this , locating shot cuts is operated by comparison tests.

In 2010, Jagadish al. [13] proposed the Lossless method of image compression and decompression using a simple coding technique called Huffman coding. This technique is simple in implementation and utilizes less memory. A software algorithm has been developed and implemented to compress and decompress the given image using Huffman coding techniques in a MATLAB platform.

In 2009, G.M.Padmaja, et al. [14] analyzes various image compression techniques. In addition, specific methods are presented illustrating the application of such techniques to the real-world images. They have presented various steps involved in the general procedure for compressing images. They provided the basics of image coding with a discussion of vector quantization and one of the main technique of wavelet compression under vector quantization. This analysis of various compression techniques provides knowledge in identifying the advantageous features and helps in choosing correct method for compression.

In 2011, S.Parveen Banu et al. [15] a novel hybrid image compression technique for efficient storage and delivery of data is proposed. It is based on decomposing the data using daubechies-4 wavelet in combination with the lifting scheme and entropy encoding. This scheme is concerned with the compression ratio, bits per pixel and peak signal to noise ratio. Experimental results illustrate that the proposed scheme is efficient and feasible in terms of compression ratio, bits per pixel and peak signal to noise ratio.

In 2011, Yu Yanxin et al. [16] presented an image compression method suited to the space-borne application. To solve the problem of large-size RS images taking up large cache, the compression scheme based on overlap blocks was taken. The overlap blocks of the image were multi-levelly decomposed by lifting wavelet. According to human visual characteristics, the lossless encoding method was used for the low-frequency sub-band most sensitive to human vision, and the bit-plane coding method was take for the remaining high-frequency sub-bands. Simulation results show that the algorithm can remove the blocking artifacts and realize the high quality image compression.

In 2011, Baluram Nagaria et al. [17] discussed the comparative study of different wavelet-based image compression systems. When wavelet transform is applied to image compression, the chosen wavelet base affects the efficiency of signal strength, pixel values and the quality of the reconstructed image, because the property parameters of different wavelet bases are varied, it is very important to research the correlation between the wavelet base properties and image compression. They have discussed various statistical numerical measures and obtained results compared in terms of MSE, PSNR, Normalization and Compression Ratio with lower and higher pixel frames. The main objective of this research measure the quality of image with statistical numerical measures (PSNR, MSE respectively) using different wavelet families with suitable decomposition level. Different test image with 512 X 512 and 1024 X1024 pixel frames are used to evaluate the performance of image compression.

In 2011, Yu Shen et al. [18] addresses Compression are useful because it helps reduce the consumption of expensive resources, such as hard disk space or transmission bandwidth. Image compression may be lossless or lossey. Lossless image compression is a class of image compression algorithms that allows the exact original data to be reconstructed from the compressed data. The term lossless is in contrast to lossy image compression, which only allows an approximation of the original data to be reconstructed, in exchange for better compression rates. Lossless compression is preferred for archival purposes and often for medical imaging, satellite imaging, or technical drawings. For the urgent requirement of efficient lossless compression and high fidelity compression, more and more research of lossless image compression will be concerned. After the introduction of the lifting scheme and the integer to integer multiwavelets, they present the approach to build integer to integer multiwavelets. In addition, experimental results of applying these multiwavelets to lossless image compression are presented.

3. Proposed Approach

In this section, we describe the proposed method. In this paper we apply a technique for image compression. Our proposed approach is the combination of walsh and wavelet transforms to make the compression better than the previous used approach. After that we apply arithmetic coding for compressing an image. The computer system has been accepted to be the very powerful mechanism to use these digital data, for its secured storage and efficient accessibility whenever required.

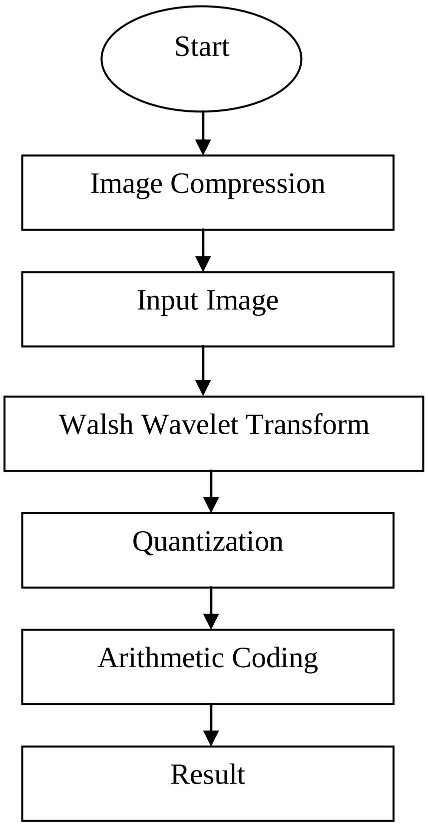

Figure 1: Flowchart of image compression

The above figure shows the working procedure
The step by step explanation is given below:

Step1: Select the input image
Step2: Set the quantization factor
Standard value of parameter is 0.02 to 0.5
(qf1>0.5 or qf1<0.02),(qf2>0.5 or qf2<0.02)
Step3: Set the compression ratio factor
Crf-range (1-10) it uses to generate quantization matrix.
Step4: Wavelet and Walsh transform for transformation, and then using Arithmetic coding for compress an image. This Compression algorithm consists of the following steps:

1. Two Levels Discrete Wavelet Transform
2. Apply 2D Walsh-Wavelet Transform on each 8x8 block of the low frequency sub band
3. Split all values form each transformed block 8x8
4. Compress each sub-band by using Arithmetic coding. The first part of WWT compression algorithm steps for high frequency, domains, and then second part of WWT compression

Steps for low frequency.
For (Low Frequency) Qf1----->LL2
For Qf2(High Frequency) Qf2 ------->HH2
and HL2 and LH2
Step5: Result shows the compressed image after the compression.

Wavelet transform is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets.

Quantization refers to the process of approximating the continuous set of values in the image data with a finite (preferably small) set of values. The input to a quantizer is the original data, and the output is always one among a finite number of levels. The quantizer is a function whose set of output values are discrete, and usually finite. Obviously, this is a process of approximation, and a good quantizer is one which represents the original signal with minimum loss or distortion. A quantizer simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of those values. Since this is a many-to-one mapping, it is a lossy process and is the main source of compression in an encoder. Quantization can be performed on each individual coefficient, which is known as Scalar Quantization (SQ).
Our Proposed Compression algorithm consists of the following steps:
1. Two Levels Discrete Wavelet Transform
2. Apply 2D Walsh Wavelet Transform on each 8x8 block of the low-frequency sub-band
3. Split all values form each transformed block 8x8
4. Compress each sub-band by using Arithmetic coding

In the below algorithm we provide the basis of accepting images from the database. In the below algorithm we want to concentrate the type of the wavelet we use which are use like db1, db2, db3 etc. Then we use the quantization factor which is QF1 and QF2 in our case. We use the value as 0.2 and 0.05 as the quantization factor.

Algorithm 1: Providing Wavelet Name and Property

Step 1: Select the input image
Image name = x
Step 2: Select the wavelet name
Wavelet name = db3
Step 3: Set the quantization factor
q1 = 0.02
qf2 = 0.5
Step 4: Set the compression ratio factor
crf = 2
Step 5: Standard value of prarameter is 0.02 to 0.5
If(wavelet name = db3) (qf1>0.5 or qf1<0.02) (qf2>0.5 or qf2<0.02)
Else
Wrong parameter enter

2-D Discrete Wavelet Transform (2-D DWT) is used in image processing as a powerful tool solving to image analysis, denoising, image segmentation and other. 2-D DWT can be applied as a convolution of a selected wavelet function with an original image or it can be seen as a set of two matrices of filters, row and column one. Using a separability property of DWT, the first part of decomposition consists of an application of row filters to the original image. The column filter is used for further processing of image resulting from the first step. This image decomposition can by mathematically described by the below equation

C=X. I. Y

where C is the final matrix of wavelet coefficients, I represents an original image, X is a matrix of row filters and Y is a matrix of column filters. In the first level of decomposition of 2D DWT, the image is separated into four parts. Each of them has a quarter size of the original image. They are called approximation coefficients (Low Low or LL), horizontal (Low High or LH), vertical (High-low or HL) and detail coefficients (High High or HH). Approximation coefficients obtained in the first level can be used for the next decomposition level. Inverse 2D Discrete Wavelet Transform used in image reconstruction is defined by the below equation

Irec = X -1 . C . Y -1

For the orthogonal matrices this formula can be simplified into below equation Arithmetic coding is similar to Huffman coding; they both achieve their compression by reducing the average number of bits required to represent a symbol.

Irec = X T . C . Y T

2-D DWT decomposition separates an image into the four parts, each of them contains different information of the original image. Coefficients represent edges in the image, approximation coefficients are supposed to be a noise. A proper modification of approximation coefficients is the easiest way for edge detection.

The principle of the simplest method of edge detection is based on replacing of all approximation coefficients by zeros. This modification removes low frequencies from the image; the image is reconstructed using only the remaining wavelet coefficients. By means of this method the most expressive edges are found.

By assigning each symbol its own unique probability range, it's possible to encode a single symbol by its range. Using this approach, we could encode a string as a series of probability ranges, but that doesn't compress anything. Instead additional symbols may be encoded by restricting the current probability range by the range of a new symbol being encoded. Below process how additional symbols may be added to an encoded string by restricting the string's range bounds. For that purpose we should use the following process.

Algorithm 2: Image Compression using Walsh

Step 1: Walsh transform is first applied on a full image.
We get the transformed image.
Step 2: The transformed image is then divided into 64 equal non-overlapping blocks.
Step 3: Energy of each block is computed as summation of square of the coefficients within that block.
Step 4: Sort all 64 blocks in ascending order according to their energies. Thus the first block in the sorted list is the lowest energy block and the last block in the sorted list is the highest energy block.
Step 5: Input number of blocks to be compressed say M.
Step6: Compress first M blocks (of the transformed

image) from the sorted list. Compressing an image is nothing but making coefficients of the selected block zero.

Step 7: Apply Inverse Walsh transform to reconstruct the image

Algorithm 3: Image Compression using Walsh Wavelet

Step 1: Walsh Wavelet Transform (WLT) is first applied on full image f of size NxN. The resultant image

F is, F = [WLT] [f] $[WLT]^T$

Step 2: The diagonal matrix D is computed as D = [WLT] $[WLT]^T$

Step 3: Compute G = [Fij /Dij] i.e. every element of transformed image F is divided by corresponding Dij value.

Where Dij = Di * Dj ; $1 \leq i \leq N$ and $1 \leq j \leq N$

Step 4: Calculate energy of each element of G as,

Eij = $[Fij / Dij]^2$ * Dij

Step 5: Divide the whole G image into 64 equal non-overlapping blocks. Compute energy of each block as summation of energy of each element within the block.

Step 6: Calculate percentage energy of each block.

Step7: Sort the blocks in ascending order of their percent energy.

Step 8: Input number of blocks to be compressed say M.

Step 9: Compress first M number of blocks from the sorted list (Make all coefficients of the block zero)

Step10:Apply inverse Walsh Wavelet transform to reconstruct the image.

Reconstructed_f = $[WLT]^T$ [G] [WLT]

lower bound = 0

upper bound = 1

so for others symbols encoding

current range = upper bound - lower bound

upper bound = lower bound + (current range × upper bound of new symbol)

lower bound = lower bound + (current range × lower bound of new symbol)

Any value between the computed lower and upper probability bounds now encodes the input string.

By definition, the encoded value lies within the lower and upper probability range bounds of the string it represents. Since the encoding process keeps restricting ranges (without shifting), the initial value also falls within the range of the first encoded symbol. Successive encoded symbols may be identified by removing the scaling applied by the known symbol. To do this, subtract out the lower probability range bound of the known symbol, and multiply by the size of the symbols' range.

Based on the discussion above, decoding a value may be performed following the steps:

1. Encoded value = Encoded input.
2. Now just identify the symbol containing encoded value within its range.
3. Remove effects of symbol from encoded value.

Current range = upper bound of new symbol - lower bound of new symbol

Encoded value = (Encoded value - lower bound of new symbol) ÷ current range

4. Result Analysis

Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. We use discrete wavelet transform so when signal is in vector form (or pixel form), the discrete wavelet transform is applied. Discrete wavelet transform is a system of filters. There are two types of filters involved, one is the wavelet filter, and the other is the scaling filter. The wavelet filter is a high pass filter, while the scaling filter is a low pass filter.

Quantization, in mathematics and digital signal processing, is the process of mapping a large set of input values to a smaller set – such as rounding values to some unit of precision. A device or algorithmic function that performs quantization is called a quantizer. The error introduced by quantization is referred to as quantization error or round-off error. Quantization is involved to some degree in nearly all digital signals processing, as the process of representing a signal in digital form ordinarily involves rounding. Quantization is the procedure of constraining something from a relatively large or continuous set of values (such as the real numbers) to a relatively small discrete set (such as the integers).

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed or reconstructed image. Compression ratio is the ratio between the compressed sizes to the decompressed size.

For the result comparison we took four different types of images which is shown in Figure 2 to Figure 5.

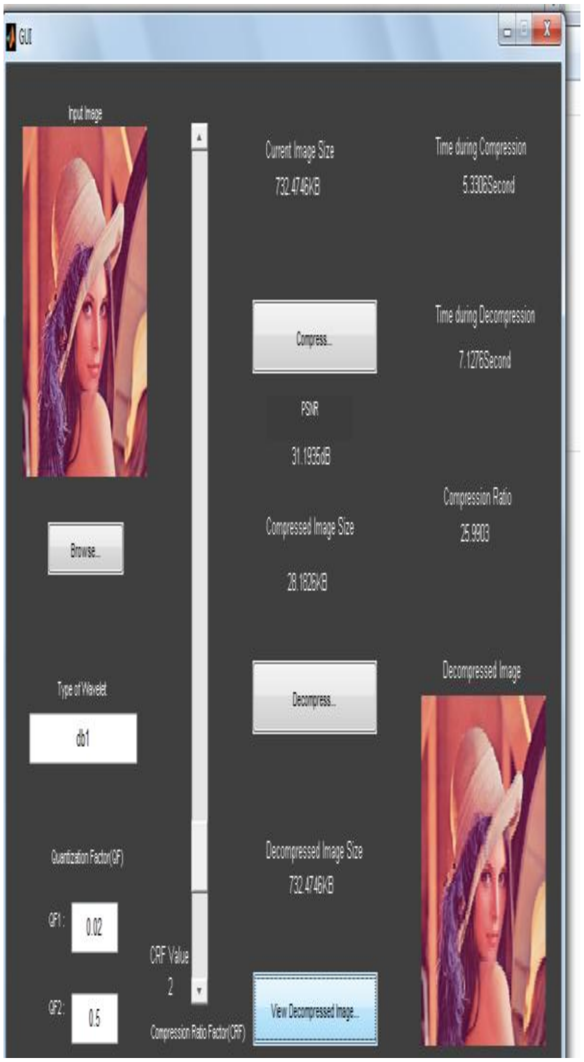

Figure 2: Leena Image

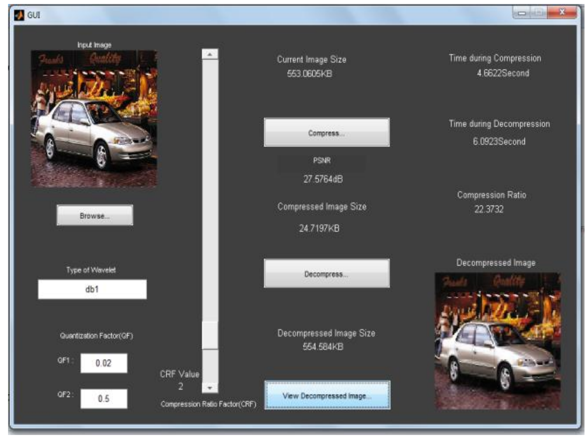

Figure 3: Car Image

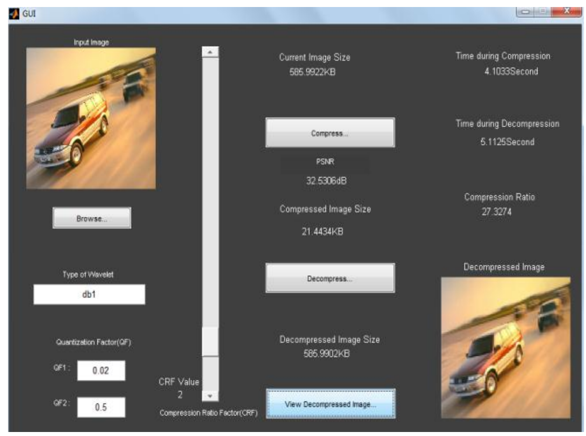

Figure 4: Scorpio Image

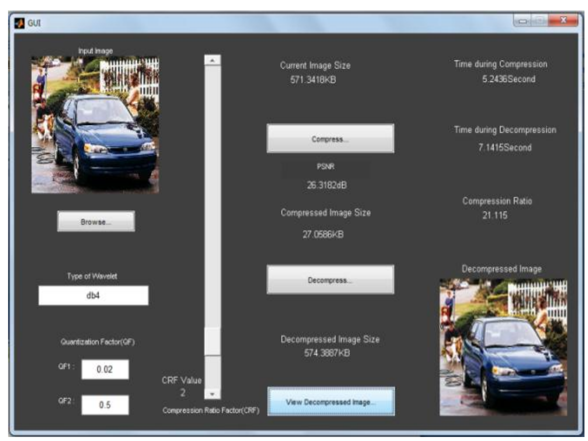

Figure 5: Mike Image

Table 1: Image compression of leena image with db1, db2, db3, db4 wavelet

Image Name	Type Of Wavelet	Current Image Size(KB)	Compressed Image Size (KB)	Time During Compression (Sec)	Time Duing Decompression (Sec)	PSNR (db)	Compression Ratio
Leena	db1	732.4746	28.1826	5.3306	7.1276	31.1935	25.9903
Leena	db2	732.4746	28.3428	5.4441	7.2094	31.0466	25.8434
Leena	db3	732.4746	26.8418	5.885	7.96	32.4918	27.2886
Leena	db4	732.4746	29.8516	5.9052	8.1143	29.7404	24.5372

Table 2: Image compression of car image with db1, db2, db3, db4 wavelet

Image Name	Type Of Wavelet	Current Image Size(KB)	Compressed Image Size (KB)	Time During Compression (Sec)	Time Duing Decompression (Sec)	PSNR (db)	Compression Ratio
Car	db1	553.0605	24.7197	4.6622	6.0923	27.5764	22.3732
Car	db2	553.0605	24.9971	4.5888	6.1025	27.3282	22.125
Car	db3	553.0605	25.1074	4.6079	6.1506	27.231	22.0278
Car	db4	553.0605	24.4268	4.5781	6.0372	27.8448	22.6416

Table 3: Image compression of Scorpio image with db1, db2, db3, db4 wavelet

Image Name	Type Of Wavelet	Current Image Size(KB)	Compressed Image Size (KB)	Time During Compression (Sec)	Time Duing Decompression (Sec)	PSNR (db)	Compression Ratio
Scorpio	db1	585.9922	21.4434	4.1033	5.1125	32.5306	27.3274
Scorpio	db2	585.9922	21.7119	3.7834	4.6983	32.1926	26.9894
Scorpio	db3	585.9922	21.2959	3.7145	4.6494	32.7199	27.5167
Scorpio	db4	585.9922	23.0898	4.1727	5.2343	30.582	25.3788

Table 4: Image compression of Mike image with db1, db2, db3, db4 wavelet

Image Name	Type Of Wavelet	Current Image Size(KB)	Compressed Image Size (KB)	Time During Compression (Sec)	Time During Decompression (Sec)	PSNR (db)	Compression Ratio
Mike	db1	571.3418	25.8896	5.1199	6.9669	27.2715	22.0683
Mike	db2	571.3418	26.4141	4.9858	6.6491	26.8334	21.6302
Mike	db3	571.3418	25.9688	4.9764	6.6372	27.2043	22.0011
Mike	db4	571.3418	27.0586	5.2436	7.1415	26.3182	21.115

Table 5: Comparison of Image compression using Walsh wavelet, DC wavelet, DCT

Image Name	Walsh Wavelet PSNR (db)	Walsh Wavelet Compression Ratio	DCT Wavelet PSNR (db)	DCT Wavelet Compression Ratio	DCT PSNR (db)	DCT Compression Ratio
Leena	31.1935	25.9903	27.1834	23.8812	24.1723	21.7603
Leena	31.0466	25.8434	27.1466	23.7323	24.1355	21.6221
Leena	32.4918	27.2886	28.5819	23.1775	24.4718	21.1645
Leena	29.7404	24.5372	24.6414	21.4361	21.5303	18.3251
Car	27.5764	22.3732	23.4653	20.2621	20.3542	17.1522
Car	27.3282	22.125	23.2171	20.1351	20.1161	17.1242
Car	27.231	22.0278	23.1312	20.1167	20.1213	17.1057
Car	27.8448	22.6416	23.7373	20.5315	20.6212	17.4214
Scorpio	32.5306	27.3274	26.4316	22.2263	23.3215	19.1152
Scorpio	32.1926	26.9894	26.1825	22.2545	23.1714	19.1442
Scorpio	32.7199	27.5167	26.6188	22.4256	23.5171	19.3145
Scorpio	30.582	25.3788	25.561	23.2677	22.1565	20.1566
Mike	27.2715	22.0683	23.2625	20.1622	20.1524	17.1411
Mike	26.8334	21.6302	22.7432	19.5221	19.6321	16.421
Mike	27.2043	22.0011	23.1132	20.1245	20.1021	17.1134
Mike	26.3182	21.115	22.2172	19.1141	19.1161	16.1032

5. Conclusion

The wavelet analysis procedure is to adopt a wavelet prototype function, called an analysing wave or mother wave. Other wavelets are produced by translation and contraction of the mother wave. A transform thus formed qualifies to be a wavelet transform if and only if it satisfies the condition of orthogonality. Thus there are only few functions which satisfy these conditions. To simplify this situation, this proposes a generalized algorithm to adopt arithmetic coding and optimization. For an NxN orthogonal transform matrix T, element of each row of T is repeated N times to generate N Mother waves. Thus rows of original transform matrix become wavelets. In this paper we explain our proposed approach which is the combination of walsh, splitting and arithmetic coding. We also include the result analysis which shows the performance of our approach.

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