Comparative Analysis Of Haar And Coiflet Wavelets Using Discrete Wavelet Transform In Digital Image Compression

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ABSTRACT

Images require substantial storage and transmission resources, thus image compression is advantageous to reduce these requirements. The objective of this paper is to evaluate a set of wavelets for image compression. Image compression using wavelet transforms results in an improved compression ratio. Wavelet transformation is the technique that provides both spatial and frequency domain information. This paper present the comparative analysis of Haar and Coiflet wavelets in terms of PSNR, Compression Ratio and Elapsed time for compression using discrete wavelet transform. Discrete wavelet transform has various advantages over Fourier transform based techniques.DWT removes the problem of blocking artifact that occur in DCT.DWT provides better image quality than DCT at higher compression ratio.

Keywords: *Image compression, Discrete Wavelet Transform, wavelet decomposition, Haar, Coiflet, Blocking Artifact*

1. INTRODUCTION

The rapid development of high performance computing and communication has opened up tremendous opportunities for various computer-based applications with image and video communication capability. However, the amount of data required to store a digital image is continually increasing and overwhelming the storage devices. The data compression becomes the only solution to overcome this. Image compression is the representation of an image in digital form with as few bits as possible while maintaining an acceptable level of image quality [1]. In a lossy compression scheme, the image compression algorithm should achieve a tradeoff between compression ratio and image quality. Higher compression ratios will produce lower image quality and vice versa. Quality and compression can also vary according to input image characteristics and content. Traditionally, image compression adopts discrete cosine transform (DCT) in most situations which possess the characteristics of simpleness and practicality. DCT has been applied successfully in the standard of JPEG, MPEGZ, etc. DCT which represent an image as a superposition of cosine functions with different discrete frequencies. The transformed signal is a function of two spatial dimensions and its components are called DCT coefficients or spatial frequencies. Most existing compression systems use square DCT blocks of regular size. The image is divided into blocks of samples and each block is transformed independently to give coefficients. To achieve the compression, DCT coefficients should be quantized. The quantization results in loss of information, but also in compression. Increasing the quantizer scale leads to coarser quantization, gives high compression and poor decoded image quality. The use of uniformly sized blocks simplified the compression system, but it does not take into account the irregular shapes within real images. However, the compression method that adopts DCT has several shortcomings that become increasing apparent. One of these shortcomings is obvious blocking artifact and bad subjective quality when the images are restored by this method at the high compression ratios. The degradation is known as the "blocking effect" and depends on block size. A larger block leads to more efficient coding, but requires more computational power. Image distortion is less annoying for small than for large DCT blocks, but coding efficiency tends to suffer. Therefore, most existing systems use blocks of 8X8 or 16X16 pixels as a compromise between coding efficiency and image quality.[4]

The Discrete Wavelet Transform (DWT) which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. The main property of DWT is that it includes neighborhood information in the final result, thus avoiding the block effect of DCT transform. It also has good localization and symmetric properties, which allow for simple edge treatment, high-speed computation, and high quality compressed image.

2. Wavelet Transform

The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The wavelet transform is often compared with the Fourier transform, in which signals are represented as a sum of sinusoids. The main difference is that wavelets are localized in both time and frequency whereas the standard Fourier transform is only localized infrequency. The Short-time Fourier transform (STFT) is more similar to the wavelet transform, in that it is also time and frequency localized, but there are issues with the frequency/time resolution trade-off. Wavelets often give a better signal representation using Multiresolution analysis, with balanced resolution at any time and frequency. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or *mother*) wavelet. Just looking at pictures of wavelets and sine waves, we can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid, just as some foods are better handled with a fork than a spoon.

2.1 DISCRETE WAVELET TRANSFORM

DWT now becomes a standard tool in image compression applications because of their data reduction capabilities. DWT can provide higher compression ratios with better image quality due to higher decorrelation property. Therefore, DWT has potentiality for good representation of image with fewer coefficients. The discrete wavelet transform uses filter banks for the construction of the multiresolution time-frequency plane. The Discrete Wavelet Transform analyzes the signal at different frequency bands with different resolutions by decomposing the signal into an approximation and detail information. The decomposition of the signal into different frequency bands obtained by successive high pass g[n] and low pass h[n] filtering of the time domain signal. The basis of Discrete Cosine Transform (DCT) is cosine functions while the basis of Discrete Wavelet Transform (DWT) is wavelet function that satisfies requirement of multiresolution analysis.[1] DWT processes data on a variable time-frequency plane that matches progressively the lower frequency components to coarser time resolutions and the high-frequency components to finer time resolutions, thus achieving a multiresolution analysis.[3] The introduction of the DWT made it possible to improve some specific applications of image processing by replacing the existing tools with this new mathematical transform. The JPEG 2000 standard proposes a wavelet transform stage since it offers better rate/distortion (R/D) performance than the traditional discrete cosine transform (DCT).[3]

Advantages : Compared with DCT, the coefficients of DWT are well localized in not only the frequency, but also the spatial domains. This frequency-spatial localization property is highly desired for image compression [2] .Images coded by DWT do not have the problem of block artifacts which the DCT approach may suffer [2].

3. WAVELET FAMILIES

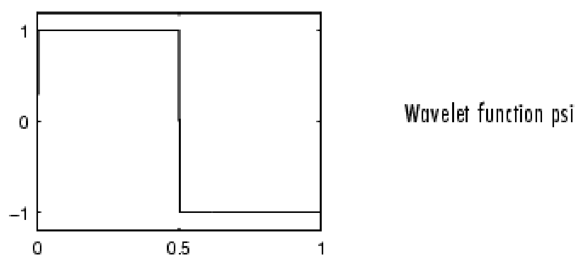
The choice of wavelet function is crucial for performance in image compression. There are a number of basis that decides the choice of wavelet for image compression. Since the wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting wavelet transform [7].

Important properties of wavelet functions in image compression applications are compact support (lead to efficient implementation), symmetry (useful in avoiding dephasing), orthogonality (allow fast algorithm), regularity, and degree of smoothness (related to filter order or filter length)

The compression performance for images with different spectral activity will decides the wavelet function from wavelet family. Daubechies and Coiflet wavelets are families of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters and, thus, lead to efficient implementation. If we want both symmetry and compact support in wavelets, we should relax the orthogonality condition and allow nonorthogonal wavelet functions. Biorthogonal wavelets, exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and the other for reconstruction. This property is used, connected with sampling problems, when calculating the difference between an expansion over the of a given signal and its sampled version instead of the same single one, interesting properties can be derived A major disadvantage of these wavelets is their asymmetry, which can cause artifacts at borders of the wavelet sub bands. The wavelets are chosen based on their shape and their ability to compress the image in a particular application [7].

3.1 Haar Wavelet

Wavelets begin with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1



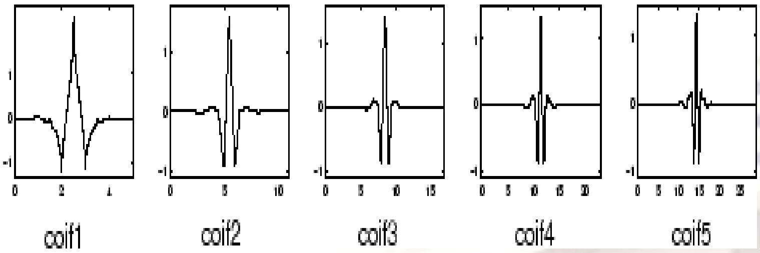
In Figure**:** Haar Wavelet Function Waveform

3.2. Coiflet Wavelets

Built by I. Daubechies at the request of R. Coif man. The wavelet function has $2N$ moments equal to 0 and the scaling function has $2N$-1 moments equal to 0. The two functions have a support of length $6N$-1.

General characteristics:

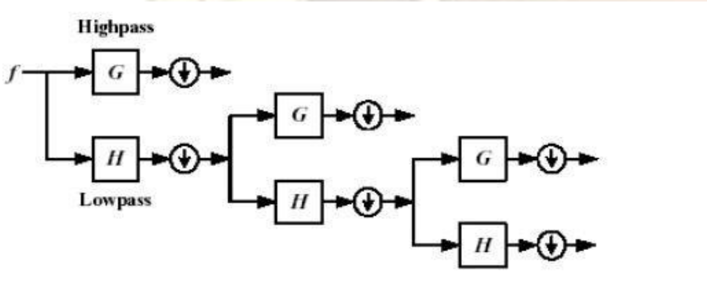
Compactly supported wavelets with highest number of vanishing moments for both phi and psi for a given support width.



In Figure: Coiflets wavelet families

4. ALGORITHM FOR IMAGE COMPRESSION USING DWT

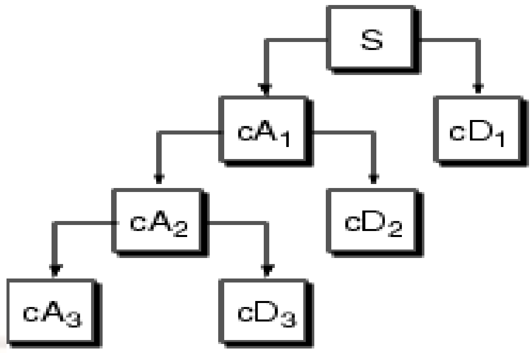
Algorithm follows a quantization approach that divides the input image in 4 filter coefficients as shown below, and then performs further quantization on the lower order filter or window of the previous step. This quantization depends upon the decomposition levels and maximum numbers of decomposition levels to be entered are 3 for DWT. This paper presents the result at 2nd and 3rd level of decomposition using different wavelets.



In Figure**:** Multilevel Decomposition using low pass and high pass filters for image compression using wavelets

4.1 Wavelet Decomposition

The composition process can be iterated with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called multiple-level wavelet decomposition.



In Figure: Decomposition Tree

5. PERFORMANCE PARAMETERS

The performance of image compression techniques are mainly evaluated by Compression Ratio (CR),PSNR and Elapsed time for compression The work has been be done in MATLAB software using image processing and Wavelet toolbox. The compressed image are reconstructed into an image similar to the original image by specifying the same DWT coefficients at the reconstruction end by applying inverse DWT. In this paper we use moon.tif image as test image for processing and compression. The compression ratio is defined as:

CR=Original data size/compressed data size

PSNR: Peak Signal to Noise ratio used to be a measure of image quality. PSNR parameter is often used as a benchmark level of similarity between reconstructed images with the original image. A larger PSNR produces better image quality.

PSNR = 10 log10

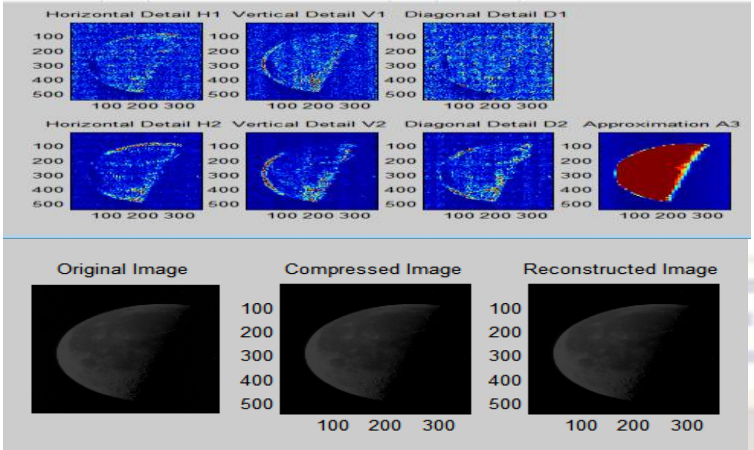
Mean square error (MSE)

6. RESULTS AND DISCUSSION

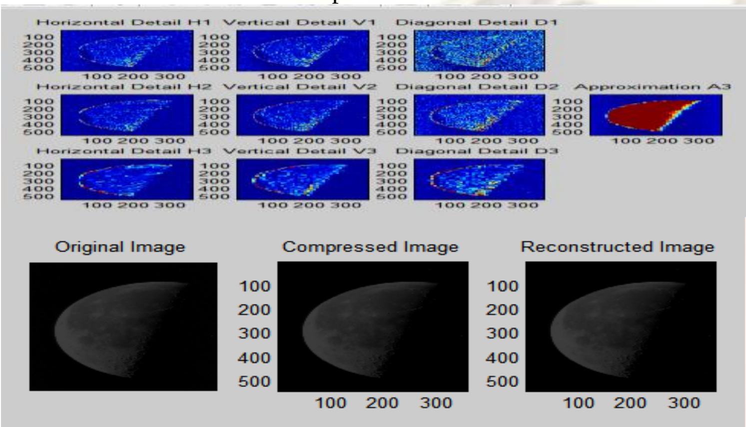
DWT technique is used for obtain the desired results. Different wavelets are used at 2nd and 3rd level of decomposition and comparative analysis of Haar and coiflets family is displayed. Quantitative analysis has been presented by measuring the values of attained Peak Signal to Noise Ratio and Compression Ratio at 2nd and 3rd decomposition levels. The intermediate image decomposition windows from various low pass and high pass filters. Qualitative analysis has been performed by obtaining the compressed version of the input image by DWT Technique and comparing it with the test image. Our results shows that Haar and Coif1 wavelet gives better result in each family and Haar wavelet gives best result as compare to coif1 wavelet in terms of compression ratio , PSNR value and take less time for compression.

QUALITATIVE ANALYSIS

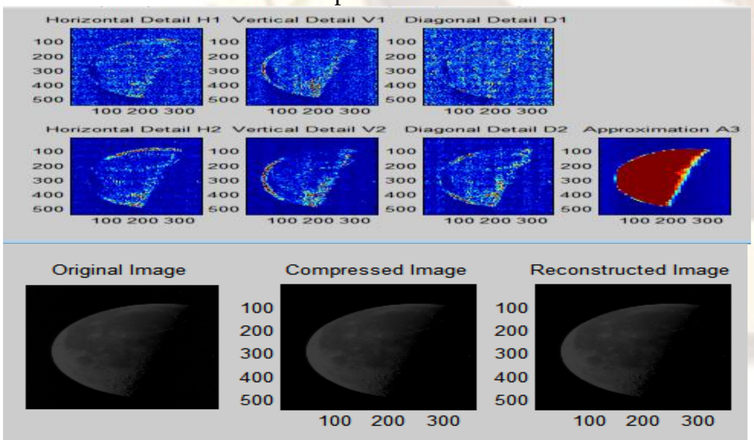
1. Using moon.tif image at 2nd level of decomposition with Haar wavelet



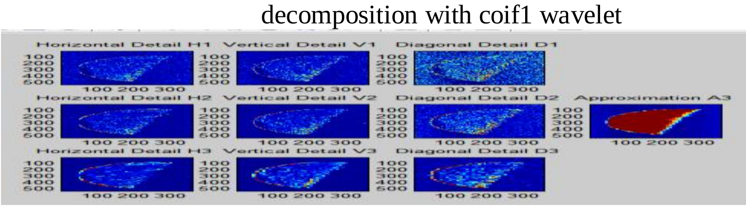
2. Using moon.tif image at 3rd level of decomposition with Haar wavelet

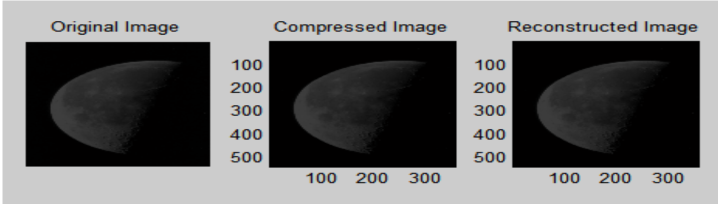


3. Using moon.tif image at 2nd level of decomposition with coif1 wavelet



4. Using moon.tif image at 3rd level of decomposition with coif1 wavelet





QUANTITATIVE ANALYSIS

Results obtain by PSNR and Compression Ratios at 2nd and 3rd levels of decompositions. Also, the elapsed time for Haar and Coiflet family (coif1, coif2, coif3, coif3, coif4, coif5) at 2nd and 3rd level of decomposition have been obtained and shown below in tabular form:

Table 1: PSNR values, Compression ratio and Computation Time (in sec) for Haar(db1) and Coiflet family Wavelet for moon.tif image

Wavelet type	Level of decomposition (Input)	Compression Ratio (Output-%)	PSNR Output-%)	Elapsed Time for compression(sec)
Haar	2	63.1034	99.9876	0.478918
	3	64.3912	99.9874	0.599028
Coif 1	2	56.0988	99.9931	0.506045
	3	57.6426	99.9929	0.607784
Coif 2	2	57.0760	99.9927	0.533141
	3	58.4245	99.9924	0.623350
Coif 3	2	57.2226	99.9923	0.566769
	3	58.4182	99.9920	0.663584
Coif 4	2	57.1455	99.9920	0.574323
	3	58.2078	99.9915	0.678074
Coif 5	2	56.9859	99.9917	0.619991
	3	58.0287	99.9917	0.744336

7. CONCLUSION

In this paper, the results are obtained at 2nd and 3rd level of decomposition, PSNR, Compression ratio and elapsed time for each wavelet is compared. From results we conclude that results obtain at 2nd level of decomposition gives better results in terms of PSNR, Compression ratio and elapsed time as compare to 3rd level of decomposition and results of Haar wavelet is better than Coiflet family. Also We see that in Coiflet family coif1 gives the better results as compare to coif2, coif3, coif4 and coif5.

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