JPEG Image Compression based on Biorthogonal, Coiflets and Daubechies Wavelet Families

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ABSTRACT
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. These properties of wavelet transform greatly help in identification and selection of significant and non-significant coefficients amongst the wavelet coefficients. DWT (Discrete Wavelet Transform) represents image as a sum of wavelet function (wavelets) on different resolution levels. So, the basis of wavelet transform can be composed of function that satisfies requirements of multiresolution analysis. The choice of wavelet function for image compression depends on the image application and the content of image. A review of the fundamentals of image compression based on wavelet is given here. This study also discussed important features of wavelet transform in compression of images. In this study we have evaluated and compared three different wavelet families i.e. Daubechies, Coiflets, Biorthogonal. Image quality is measured, objectively using peak signal-to-noise ratio, Compression Ratio and subjectively using visual image quality.

Keywords
DCT, wavelets, wavelet transform, Image compression, compression performance, image quality.

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]. A typical still image contains a large amount of spatial redundancy in plain areas where adjacent picture elements i.e. the pixels have almost the same values. It means that the picture elements are highly correlated. The redundancy can be removed to achieve compression of the image data i.e., the fundamental components of compression are redundancy and irrelevancy reduction. The basic measure of the performance of a compression algorithm is the compression ratio, which is defined by the ratio between original data size and compressed data size. Higher compression ratios will produce lower image quality and the vice versa is also true.

Current standards for compression of images use DCT [2-4], 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. DCT coefficients measure the contribution of the cosine functions at different discrete frequencies. DCT provides excellent energy compaction and a number of fast algorithms exist for calculating the DCT. 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. The block-based segmentation of source image is a fundamental limitation of the DCT-based compression system. 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.

Wavelets provide good compression ratios, especially for high resolution images. Wavelets perform much better than competing technologies like JPEG 10 both in terms of signal-to-noise ratio and visual quality. Unlike JPEG, it shows no blocking effect but allow for a graceful degradation of the whole image quality, while preserving the important details of the image. The next version of the JPEG standard i.e. JPEG 2000 will incorporate wavelet based compression techniques. In a wavelet compression system, the entire image is transformed and compressed as a single data object rather than block by block as in a DCT-based compression system. It allows a uniform distribution of compression error across the entire image. It can provide better image quality than DCT, especially on a higher compression ratio. However, the implementation of the DCT is less expensive than that of the DWT. For example, the most efficient algorithm for 2-D 8X8 DCT requires only 54 multiplications, while the complexity of calculating the DWT depends on the length of wavelet filters. A wavelet image compression system can be consists of wavelet function, quantizer and an encoder. In our study, we used various wavelets for image compression on image test set and then evaluate and compare the wavelets. According to this analysis, we show the choice of the wavelet for image compression taking into account objective image quality measures [5].

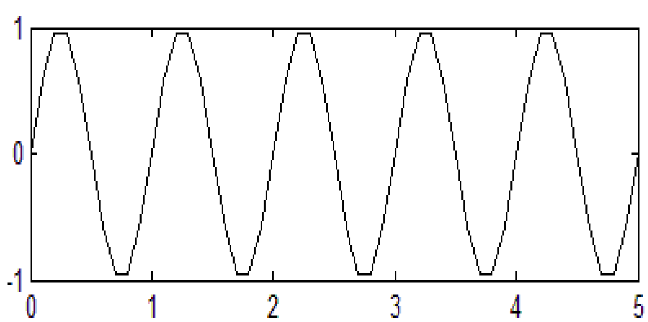
2. WAVELET TRANSFORM

The signal is defined by a function of one variable or many variables. Any function is represented with the help of basis function. An impulse is used as the basis function in the time domain. Any function can be represented in time as a summation of various scaled and shifted impulses. Similarly the sine function is used as the basis in the frequency domain. However these two-basis functions have their individual weaknesses: an impulse is not localized in the frequency domain, and is thus a poor basis function to represent frequency information. Likewise a sine wave is not localized in the time domain [6]. In order to represent complex signals efficiently, a basis function should be localized in both time and frequency domains. The support of such a basis function should be variable, so that a narrow version of the function can be used to represent the high frequency components of a signal while wide version of the function can be used to represent the low frequency components. Wavelets satisfy the conditions to be qualified as the basis functions.

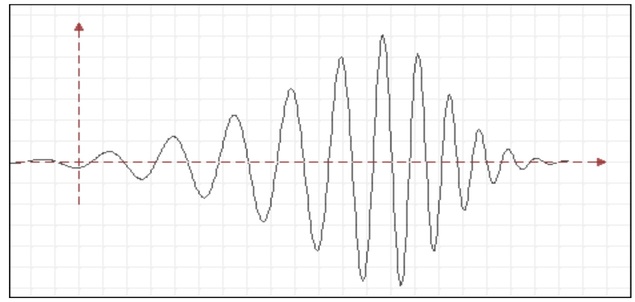
Sinusoidal wave is one of the popular waves, which extend from -∞ to +∞. Sinusoidal signals are smooth and predictable; it is the basis function of Fourier analysis. Fourier analysis consists of breaking up a signal into sine and cosine waves of various frequencies. A wavelet is waveform of limited duration that has an average value of zero. Wavelets are localized waves and they extend not from -∞ to +∞ but only for finite time duration, as shown in Fig. 2. A wavelet is a waveform of effectively limited duration that has an average value of zero. Compare wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration -- they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

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.

It also makes sense that local features can be described better with wavelets that have local extent.



(a) A Wave



(b) Wavelet

Figure 2.1 (a) A wave (b) Wavelet

The wavelet as shown in Fig. 2.1. is a mother wavelet (*h (t)*). The mother wavelet and its scaled daughter functions are used as a basis for a new transform.

Unfortunately, if *h(t)* is centered around t = 0, with extension between – T and + T, no matter how many daughter wavelets we use, it will not be possible to properly represent any point at t >T of a signal s(t). For the case using a localized wave or wavelet, it must be possible to shift the center location of the function. In other words, it must include a shift parameter, b, and the daughter wavelets should be defined as

The reason for choosing the factor in the above equation is to keep the energy of the daughter wavelets constant.

$$h_{ab}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right)$$

3. WAVELET TRANSFORM VERSES FOURIER TRANSFORM

3.1 Time Frequency Resolution

In the well-known Fourier analysis, a signal is broken down into constituent sinusoids of different frequencies. These sines and cosines (essentially complex exponentials) are the basis functions and the elements of Fourier synthesis. Taking the Fourier transform of a signal can be viewed as a rotation in the function space of the signal from the time domain to the frequency domain. Similarly, the wavelet transform can be viewed as transforming the signal from the time domain to the wavelet domain. This new domain contains more complicated basis functions called wavelets, mother wavelets or analyzing wavelets.

A major drawback of Fourier analysis is that in transforming to the frequency domain, the time domain information is lost. When looking at the Fourier transform of a signal, it is impossible to tell when a particular event took place. In an effort to correct this deficiency, Dennis Gabor (1946) adapted the Fourier transform to analyze only a small section of the signal at a time. a technique called windowing the signal [14]. Gabor.s adaptation, called the Windowed Fourier Transform (WFT) gives information about signals simultaneously in the time domain and in the frequency domain To illustrate the time-frequency resolution differences between the Fourier transform and the wavelet transform consider the following figures.

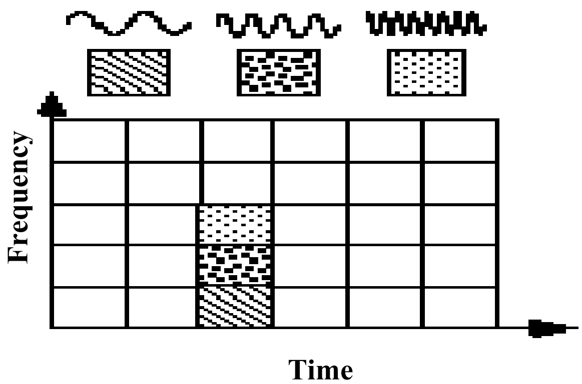


Figure 3.1 WFT Resolution

Figure 3.1 shows a windowed Fourier transform, where the window is simply a square wave. The square wave window truncates the sine or cosine function to fit a window of a particular width. Because a single window is used for all frequencies in the WFT, the resolution of the analysis is the same at all locations in the time frequency plane. An advantage of wavelet transforms is that the windows vary. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones.

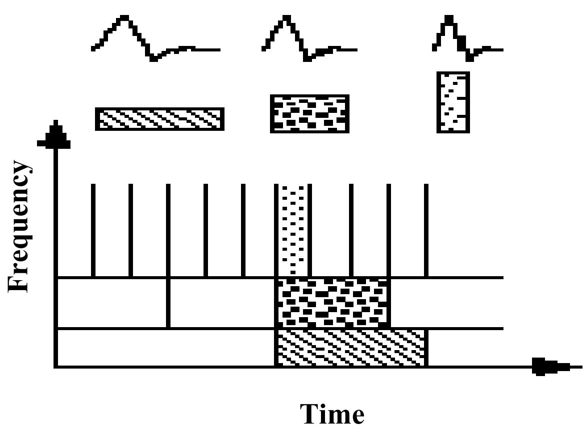


Figure 3.2 Wavelet Transform

Figure 3.2 shows a time-scale view for wavelet analysis rather than a time frequency region. Scale is inversely related to frequency. A low-scale compressed wavelet with rapidly changing details corresponds to a high frequency. A high-scale stretched wavelet that is slowly changing has a low frequency application.

4. WAVELET FAMILIES

4.1 Biorthogonal Wavelets

This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived.

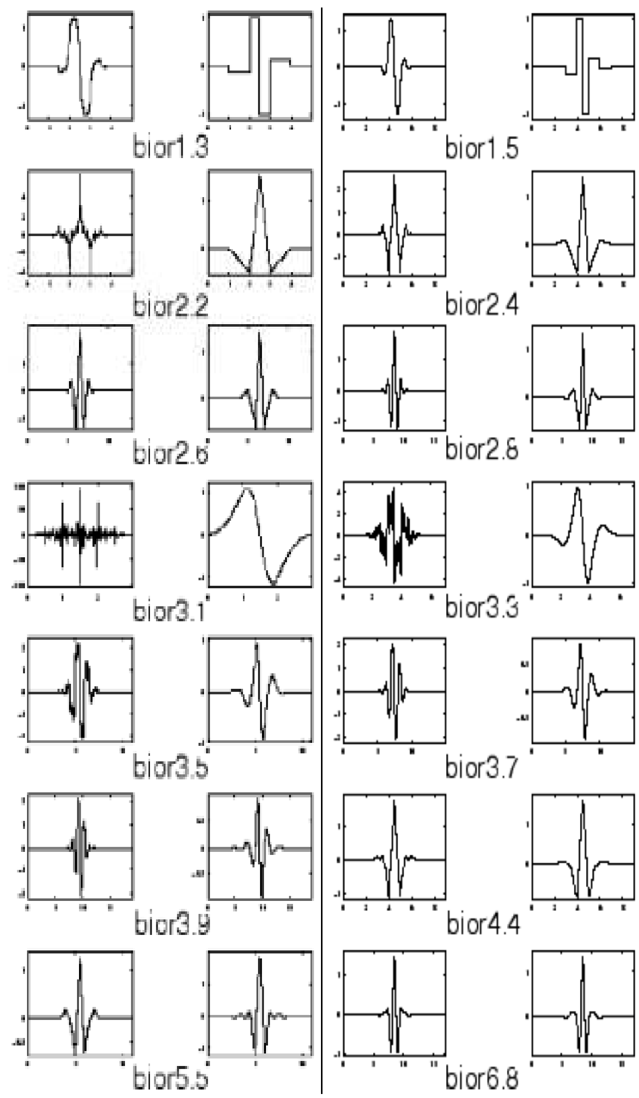


Figure 4.1 Biorthogonal wavelet Families

4.2 Coiflets Wavelets

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.

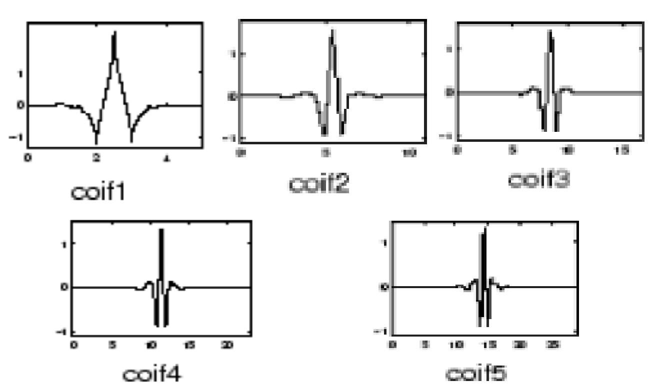


Figure 4.2 Coiflets Wavelet Families

4.3 Daubechies Wavelets

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets — thus making discrete wavelet analysis practicable.The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here is the wavelet functions psi of the next nine members of the family:

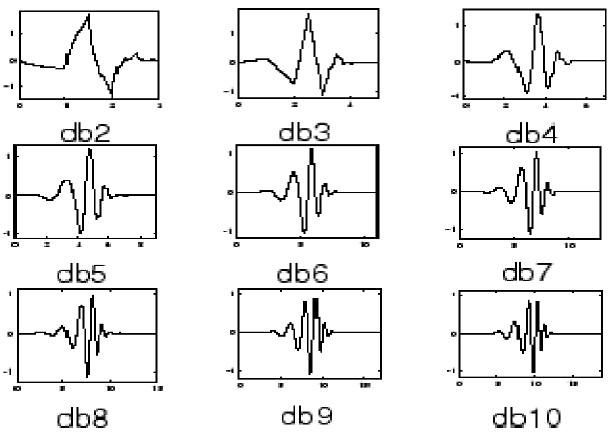


Figure 4.3 Daubechies Wavelet Families

5. DISCRETE WAVELET TRANSFORM

The transform based coding techniques work by statistically de-correlating the information contained in the image so that the redundant data can be discarded [5]. Therefore a "dense" signal is converted to a "sparse" signal and most of the information is concentrated on a few significant coefficients. The greatest problem associated with the transform coding techniques such as DCT based image compression [6-8] is the presence of visually annoying "blocking artifact" in the compressed image. This has caused an inclination towards the use of Discrete Wavelet Transform (DWT) for all image and video compression standards. DWT offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies).In present scene, much of the research works in image compression have been done on the Discrete Wavelet Transform. DWT now becomes a standard tool in image compression applications because of their data reduction capabilities. 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 multi-resolution analysis [9]. Discrete wavelet transform have certain properties that makes it better choice for image compression. It is especially suitable for images having higher resolution. DWT represents image on different resolution level i.e., it possesses the property of Multi-resolution. Since, DWT can provide higher compression ratios with better image quality due to higher de-correlation property. Therefore, DWT has potentiality for good representation of image with fewer coefficients. DWT Converts an input series x0, x1,xm, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

$$H_1 = \sum_{m=0}^{k-1} x_{2i-m} . s_m(z)$$

$$L_1 = \sum_{m=0}^{k-1} x_{2i-m} . t_m(z)$$

Where Sm (Z) and tm (Z) are called wavelet filters, K is the length of the filter, and i=0, [n/2]-1.

In practice, such transformation will be applied recursively on the low-pass series until the desired number of iterations is reached.

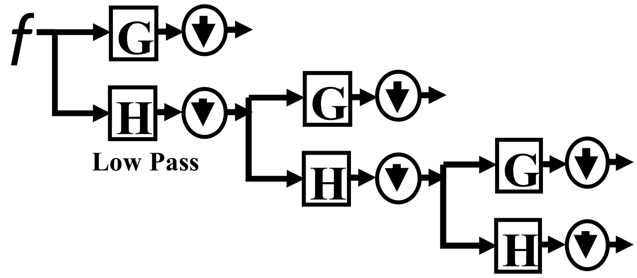


Figure. 5.1 Filter Iteration Series

6. IMAGE COMPRESSION USING 2D-DWT

A wavelet image compression system can be created by selecting a type of wavelet function, quantizer, and statistical coder. In this paper, we do not intend to give a technical description of a wavelet image compression system. We used a few general types of wavelets and compared the effects of wavelet analysis and representation, compression ratio, image content, and resolution to image quality [10]. According to this analysis, we show that searching for the optimal wavelet needs to be done taking into account not only objective picture quality measures, but also subjective measures. We highlight the performance gain of the DWT over the DCT.

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 [11]. Therefore, the details of the particular application should be taken into account and the appropriate wavelet should be chosen in order to use the wavelet transform effectively for image compression. The compression performance for images with different spectral activity will decides the wavelet function from wavelet family. In our experiment multiple wavelet functions of wavelet families are examined namely: Daubechies, bior, & Coiflet.Daubechies wavelets are the most popular wavelets. Biorthogonal wavelets, exhibits the property of linear phase, which is needed for signal and image reconstruction. Coiflets are discrete wavelets designed by Ingrid Daubechies.The wavelet is near symmetric their wavelet functions have N\3 vanishing moments. The coif N and are much more symmetrical than the dbNs where N is the order of family. 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 [12].

6.1 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.

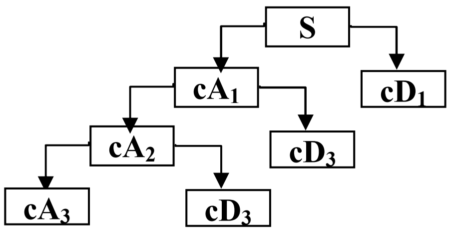


Figure 6.1 Decomposition Tree

7. PERFORMANCE EVALUATION METHODOLOGY

The performance of image compression techniques are mainly evaluated by the two measures: Compression Ratio (CR) and the magnitude of error introduced by the encoding.

The compression ratio is defined as:

$$CR = \frac{\text{The number of bits in the original image}}{\text{The number of bits in the compressed image}}$$

For error evaluation, two error metrics are used to compare the various image compression techniques: Mean Square Error (MSE) and the Signal to Noise Ratio (SNR). SNR is used to measure the difference between two images. In order to quantitatively evaluate the quality of the compressed image the Signal-to-Noise Ratios (SNR) of the images are computed. SNR provides a measurement of the amount of distortion in a signal [4], with a higher value indicating less distortion. For n-bits per pixel image, SNR is defined as [13]:

$$SNR = 20\log_{10}\frac{2^n}{MSE}$$

8. EXPERIMENT RESULTS & DISCUSSIONS

8.1 Image Compression Using DWT

In this study, we have examined three types of wavelet families: Daubechies Wavelet, Coiflet Wavelet, and Biorthogonal Wavelet. We have analyzed three different test images: Cell (159X191), Pout (291X240), and Saturn (328X438). Results are measured in terms of Signal to Noise Ratio (SNR), Compression Ratio (CR) and visual quality of compressed image. The comparison of CR & SNR values of wavelets of each wavelet family for different test images shown in figures. Figure 8.1 shows the Compression Ratio & PSNR value of the cell image similarly Figure 8.2 & Figure 8.3 shows the value of CR & PSNR in case of pout and Saturn image. Table 1 shows the different values of CR, PSNR for biorthogonal & Coiflets & Daubechies Wavelet families for cell image. Similarly Table 2 & Table 3 contains the values of CR & PSNR for pout & Saturn image.Biorthogonal has Bior 1.1,bior 1.3,bior 1.5,bior 2.2,bior 2.4,bior 2.6,bior 2.8,bior 3.1,bior 3.3,bior 3.5,bior 3.7,bior 3.9,bior 4.4,bior 5.5 & bior 6.8 wavelet families & coiflets has coi 1,coi 2,coi 3,coi 4 & coi 5. Wavelet families also daubechies wavelet has db 1, db 2, db 4, db 5, db 6, db 8, db 10, db 15, db 16, db 32.

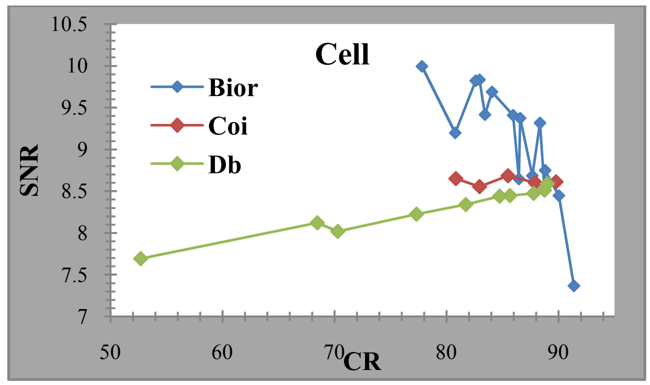


Figure 8.1. SNR & CR of cell image for biorthogonal, Coiflets & Daubechies wavelet.

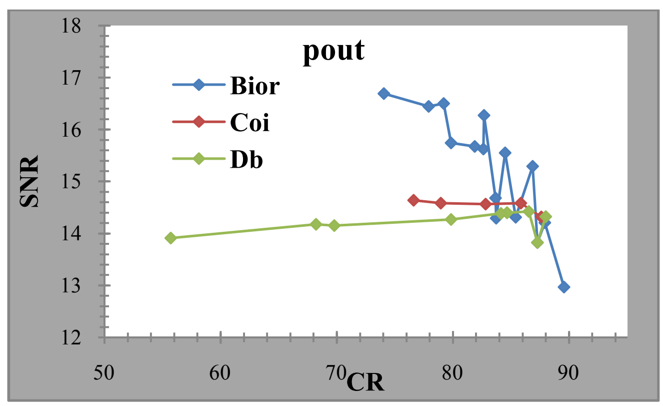


Figure 8.2. SNR & CR of pout image for Biorthogonal Coiflets & Daubechies wavelet.

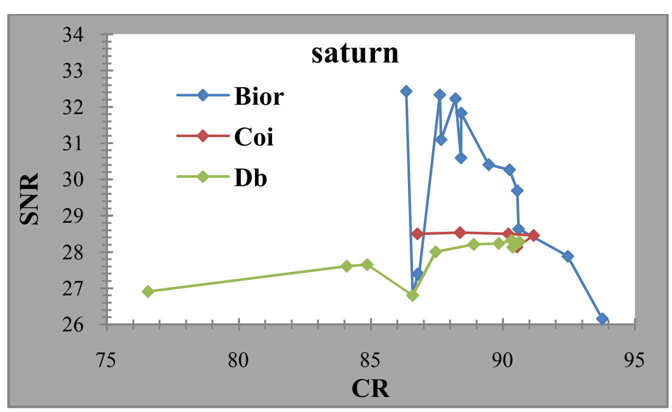


Figure 8.3. SNR & CR of Saturn image for Biorthogonal, Coiflets & Daubechies Wavelet.

Table 1: Value of CR, PSNR & SNR OF "Cell IMAGE" USING different Wavelet families

S. No.	Biorthogonal				Coiflets				Daubechies			
	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR
1	Bior 1.1	88.7588	33.4990	8.5140	Coi 1	89.7770	33.5960	8.6109	Db 01	88.7588	33.4990	8.5140
2	Bior 1.3	88.8215	33.7365	8.7514	Coi 2	87.9276	33.5865	8.6014	Db 02	88.9964	33.5738	8.5887
3	Bior 1.5	87.6750	33.6707	8.6856	Coi 3	85.5066	33.6689	8.6838	Db 04	87.7697	33.4578	8.4727
4	Bior 2.2	88.3489	34.3007	9.3152	Coi 4	82.9440	33.5380	8.5529	Db 05	85.6539	33.4323	8.4473
5	Bior 2.4	86.5733	34.3598	9.3743	Coi 5	80.8486	33.6334	8.6484	Db 06	84.7630	33.4262	8.4412
6	Bior 2.6	85.9404	34.3915	9.4060					Db 08	81.7179	33.3267	8.3416
7	Bior 2.8	83.4448	34.4005	9.4150					Db 10	77.3059	33.2089	8.2238
8	Bior 3.1	80.7806	34.1836	9.1985					Db 15	70.2901	33.0034	8.0183
9	Bior 3.3	84.0690	34.6726	9.6871					Db 16	68.4673	33.1058	8.1207
10	Bior 3.5	82.6020	34.8046	9.8195					Db 32	52.6860	32.6773	7.6922
11	Bior 3.7	82.9576	34.8186	9.8331								
12	Bior 3.9	77.7927	34.9769	9.9914								
13	Bior 4.4	90.0439	33.4339	8.4488								
14	Bior 5.5	91.3779	32.3524	7.3673								
15	Bior 6.8	86.4629	33.6316	8.6465								

Table 2: Value of CR, PSNR & SNR OF "Pout IMAGE" USING different Wavelet families

S. No.	Biorthogonal				Coiflets				Daubechies			
	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR
1	Bior 1.1	87.2825	33.9909	13.8298	Coi 1	87.6308	34.482	14.3210	Db 01	87.2825	33.9909	13.8298
2	Bior 1.3	85.4161	34.4734	14.3124	Coi 2	85.8457	34.7469	14.5859	Db 02	88.0164	34.4902	14.3292
3	Bior 1.5	83.7416	34.4565	14.2954	Coi 3	82.8216	34.7311	14.5701	Db 04	86.5505	34.5891	14.4280
4	Bior 2.2	86.873	35.4591	15.2980	Coi 4	78.9678	34.7466	14.5855	Db 05	84.6591	34.561	14.4000
5	Bior 2.4	84.5118	35.7131	15.5520	Coi 5	76.6118	34.7995	14.6385	Db 06	84.1412	34.5494	14.3883
6	Bior 2.6	81.8908	35.8394	15.6784					Db 08	79.8481	34.4311	14.2701
7	Bior 2.8	79.8618	35.9038	15.7428					Db 10	84.6591	34.561	14.4000
8	Bior 3.1	82.6362	35.79	15.6290					Db 15	69.8004	34.3169	14.1559
9	Bior 3.3	82.6989	36.4383	16.2773					Db 16	68.2089	34.3374	14.1763
10	Bior 3.5	79.2208	36.6642	16.5032					Db 32	55.7206	34.0731	13.9120
11	Bior 3.7	77.9105	36.6097	16.4487					Db45	13.6082	6.4504	-13.7107
12	Bior 3.9	74.0749	36.8533	16.6923								
13	Bior 4.4	87.9082	34.3724	14.2113								
14	Bior 5.5	89.5795	33.1339	12.9729								
15	Bior 6.8	83.6676	34.8471	14.6860								

Table 3: Value of CR, PSNR & SNR OF "Saturn IMAGE" USING different wavelet families

S. No.	Biorthogonal				Coiflets				Daubechies			
	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR	Wavelet	CR	PSNR	SNR
1	Bior 1.1	86.5844	35.4102	26.8064	Coi 1	90.5244	37.0456	28.1383	Db 01	86.5844	35.4102	26.8064
2	Bior 1.3	86.8167	35.9786	27.3749	Coi 2	91.1516	37.0598	28.456	Db 02	90.3647	36.7295	28.1257
3	Bior 1.5	86.7724	36.0021	27.3984	Coi 3	90.2038	37.1005	28.4968	Db 04	90.6163	36.884	28.2803
4	Bior 2.2	90.5343	38.2953	29.6916	Coi 4	88.3692	37.101	28.5302	Db 05	90.3374	36.9242	28.3204
5	Bior 2.4	90.2474	38.8694	30.2657	Coi 5	86.7603	37.1015	28.4978	Db 06	89.834	36.8352	28.2314
6	Bior 2.6	89.466	39.0122	30.4085					Db 08	88.8889	36.8113	28.2075
7	Bior 2.8	88.4124	39.1934	30.5896					Db 10	87.4486	36.6079	28.0042
8	Bior 3.1	87.655	39.7006	31.0969					Db 15	84.8567	36.2541	27.6504
9	Bior 3.3	88.4202	40.4314	31.8277					Db 16	84.0811	36.209	27.6052
10	Bior 3.5	88.2056	40.8251	32.2213					Db 32	76.5657	35.5105	26.9067
11	Bior 3.7	87.6074	40.9326	32.3289								
12	Bior 3.9	92.4471	36.4811	27.8774								
13	Bior 4.4	86.3357	41.0353	32.4316								
14	Bior 5.5	93.759	34.7608	26.1571								
15	Bior 6.8	90.5895	37.2343	28.6306								

9. CONCLUSION

Image Compression using DWT has various advantages over DCT [12-14].In case of image compression DWT no need to divide the input coding into non-overlapping 2-D blocks, it has higher compression ratios avoid blocking artifacts. Also allows good localization both in time and spatial frequency domain. Better identification of which data is relevant to human perception→ higher compression ratio

The discrete wavelet transform performs very well in the compression of image signals. The performance measure results are obtained using the Biorthogonal, Coiflets & Daubechies Wavelet Families on to three different images Cell (159X191), Pout (291X240) and Saturn (338X438). The Compression results are measured in terms of CR, SNR. The Experimental results are discussed here for all three images.

CASE -1(Cell image) : In case of Cell image having less pixel size(159X191) bior_2.2 ,Coi_1 & Db_2 provides the better compression ratio, & SNR. However, bior_2.2 is most efficient wavelet family for compressing low resolution images. With Coi_1, compression ratio is higher but SNR is less compared to bior_2.2. Similarly for Db_2, CR high but image quality is low. Among other wavelets Coi_1and bior_3.3 gives high SNR but Compression Ratio achieved is comparatively low.

CASE-2(Pout Image): For medium pixel size images such as pout (291X240) bior_2.2. , Coi_1 & Db_2 provides better results as is the case for low pixel size Cell image.

CASE-3(Saturn image): For high pixel size images such as Saturn (338X438) Coi_2 provides better Compression ratio as compared to the biorthogonal & Daubechies families. Bior_2.2 & Db_2 also provides good compression ratio but comparatively less than Coi_2.

Finally, it can concluded that for low pixel size image biorthogonal wavelet is best among all the families and for high pixel size image coiflets is better suited. In case of medium size images, both daubechies & biorthogonal provides better results. Simulation results prove the effectiveness of DWT based techniques in attaining an efficient compression ratio, achieving higher signal to noise ratio and better peak signal to noise ratio (PSNR), while the retained signal energy is 99.94% and image quality is much smoother. Biorthogonal has the highest compression ratio & signal to noise ratio. Results are also tested through the wavelet toolbox which has given the higher energy ratio. As wavelet image compression has revolutionized image compression field with unbelievable results. This involves the state of art techniques but wavelet decomposition remains the initial step for all these including wavelet packets techniques. Therefore there was a need to exploit the inherent ability of wavelets.

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