Low Bit Rate Video Coding Implementation Using Wavelet Transform

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ABSTRACT
One of advanced form of compression is wavelet compression. JPEG 2000 is presented as an example of modern wavelet-based image compression. JPEG 2000 image compression standard makes use of DWT (Discrete Wavelet Transform). Image compression using wavelet transforms results in an improved compression ratio. 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. DWT can be used to reduce the image size without losing much of the resolutions computed. Thus it reduces the amount of memory required to represent given image. This paper presents a review of the fundamentals of image compression based on wavelet. This paper presents low bit rate video coding based on wavelet image compression. The superior performance of DWT is demonstrated with simulation results. In this study we have evaluated and compared three different wavelet families i.e. Daubechies, Coiflets, Biorthogonal. Image quality is measured using peak signal-to-noise ratio, compression ratio and also using visual image quality.

General Terms
compression, resolution, performance, image quality.

Keywords
Discrete wavelet transform (DWT), JPEG2000, subband encoding, multiresolution, low bit rate video coding, peak signal-to-noise ratio, compression ratio.

1. INTRODUCTION
Signals are often processed in time-domain, but for some applications it is necessary to transform them in other domain like frequency domain. Fourier transform converts a signal from time domain to frequency domain, such that the frequency spectrum of a signal can be seen. However the Fourier transform cannot provide information on which frequencies occur at specific times in the signal as time and frequency are viewed independently [5]. This is the basis of the idea of formation of windows through which different parts of a signal can be viewed. For a given window in time, signal frequencies can be viewed. Method of multiresolution is thus required, which allows certain parts of the signal to be resolved well in time, and other parts to be resolved well in frequency. Wavelet analysis is exactly this multiresolution.

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.

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. 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.

1.1 Multiresolution and Wavelet Transform
The power of Wavelets comes from the use of multiresolution. Rather than examining entire signals through the same window, different parts of the wave are viewed through different size windows (or resolutions). High frequency parts of the signal use a small window to give good time resolution; low frequency parts use a big window to get good frequency information. An important thing to note is that the 'windows' have equal area even though the height and width may vary in wavelet analysis. Wavelet transform is capable of providing the time-frequency information simultaneously, hence giving a time-frequency representation of the signal. Image data compression is concerned with minimizing the number of bits required to represent an image without any appreciable loss of information. Wavelet transform makes even easier to compress, transmit and analyse many images.

1.2 Low bit rate video coding

Coding for low bit rate video applications has gained a special interest among the video coding community especially with the emergence of many applications such as videoconferencing, video telephony, surveillance, and monitoring. In each case, video and audio information are transmitted over telecommunications links, including networks, telephone lines, ISDN and radio. The bandwidth required for the transmission of digital video is very much insufficient, so the compression of digital video is required to reduce the rate of information that is to be transmitted using the telecommunications links. In low bit rate coding, DCT (discrete cosine transform) suffers from blocking effect, but video coding with wavelet transform can solve this problem in certain extent.

1.3 Discrete Wavelet Transform (DWT)

As per [1], The EPWT is a locally adaptive wavelet transform. It works along pathways through the array of function values and exploits the local correlations of the given data in a simple appropriate manner.. The experimental results show that PSNR-value obtained by applying a 9/7 tensor product wavelet transform to the original image is 24.61 dB. The EPWT provides very good approximation results but produces a non-negligible amount of extra costs due to the adaptivity of the method.

In [2], paper presented an algorithm which is based on a hybrid technique implementing a combination of the discrete wavelet transform and the discrete cosine transform Wavelet transform enables to decorrelate the spatial correlation of pixels without the limitation of the block-based DCT. Hence, undesirable blocking artifacts in the reconstructed image, typical to DCT-based compression techniques, are avoided. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. After each filtering step, half of the samples can be eliminated according to the Nyquist's rule. Experimental results shows that the DCT-DWT hybrid compression technique provides higher PSNR values of about 2–5 dB than the MPEG-based technique.

In [4], different image compression standards are illustrated. Out of which JPEG2000 is recent and new standard uses discrete wavelet transform. The wavelet transform can be performed with reversible filters, which provide for lossless coding, or non – reversible filters, which provide for higher coding efficiency without the possibility to do lossless..

According to [6] "Image compression algorithms aim to remove redundancy in data in a way which makes image reconstruction possible." This basically means that image compression algorithms try to exploit redundancies in the data; they calculate which data needs to be kept in order to reconstruct the original image and therefore which data can be 'thrown away'. By removing the redundant data, the image can be represented in a smaller number of bits, and hence can be compressed.

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 Wavelet Transform (DWT) is wavelet function that satisfies requirement of multi-resolution analysis. 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

2. 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 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. 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. This paper highlights the performance gain of the DWT.

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. 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 order to process an image, symmetric biorthogonal wavelets are used. These have two father and two mother wavelets, and are required in order to compress a matrix of data. The Daubechies wavelet family is the most widely used wavelet for image compression, with six coefficients and biorthogonality. 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 coifN and are much more symmetrical than the dbNs where N is the order of family. 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 particular application.

The compression steps needed to design wavelet based encoder is discussed in this paper.

2.1 Image compression using Discrete Wavelet Transform

Wavelet Transform has become an important method for image compression. Wavelet based coding provides substantial improvement in picture quality at high compression ratios mainly due to better energy compaction property of wavelet transforms. Wavelet transform partitions a signal into a set of functions called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies.

2.2 Subband coding

A signal is passed through a series of filters to calculate DWT. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response h(n).Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter.

$$x[n]*h[n]=\sum_{k=-\infty}^{\infty} x[k].h[n-k] \qquad (1)$$

A half band low pass filter removes all frequencies that are above half of the highest frequency in the tile signal. Then the signal is passed through high pass filter. The two filters are related to each other as

$$h[L-1-n]=(-1)^n g(n) \qquad (2)$$

Filters satisfying this condition are known as quadrature mirror filters. After filtering half of the samples can be eliminated since the signal now has the highest frequency as half of the original frequency. The signal can therefore be subsampled by 2, simply by discarding every other sample. This constitutes 1 level of decomposition and can mathematically be expressed as

$$Y1[n]=\sum_{k=-\infty}^{\infty} x[k]h[2n-k] \qquad (3)$$

$$Y2[n]=\sum_{k=-\infty}^{\infty} x[k]g[2n+1-k] \qquad (4)$$

Where y1[n] and y2[n] are the outputs of low pass and high pass filters, respectively after subsampling by 2. This decomposition halves the time resolution since only half the number of sample now characterizes the whole signal. Frequency resolution has doubled because each output has half the frequency band of the input. This process is called as sub band coding. It can be repeated further to increase the frequency resolution as shown by the filter bank.

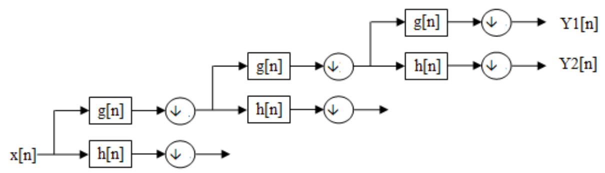

Fig.1 frequency resolution by filter bank [C.S. Burrus, R.A.Gopinath and H.Guo , Introduction to Wavelets and Wavelet Transforms, Prentice Hall, 1998.]

3. COMPRESSION STEPS

3.1 Thresholding

In certain signals, many of the wavelet coefficients are close or equal to zero. Through a method called thresholding, these coefficients may be modified so that the sequence of wavelet coefficients contains long strings of zeros. Through a type of compression known as entropy coding, these long strings may be stored and sent electronically in much less space. There are different types of thresholding. In hard thresholding, a tolerance is selected. Any wavelet whose absolute value falls below the tolerance is set to zero with the goal to introduce many zeros without losing a great amount of detail. There is not a straightforward easy way to choose the threshold, although the larger the threshold that is chosen the more error that is introduced into the process. Another type of thresholding is soft thresholding. Once again a tolerance, h, is selected. If the absolute value of an entry is less than the tolerance, than that entry is set to zero. Soft thresholding can be thought of as a translation of the signal toward zero by the amount h. Wavelets and thresholding help process the signal, but up until this point, no compression has yet occurred. One method to compress the data is Huffman entropy coding. With this method, and integer sequence, q, is changed into a shorter sequence, e, with the numbers in e being 8 bit integers. The conversion is made by an entropy coding table. Strings of zeros are coded by the numbers 1 through 100, 105, and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254.

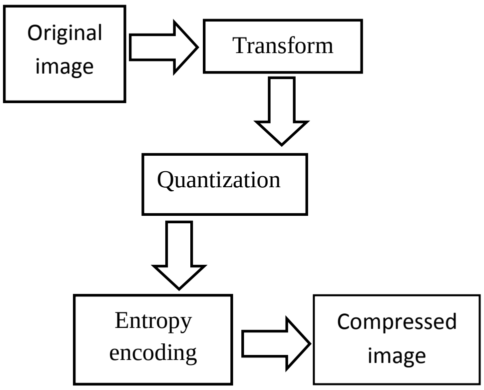

Fig 2 image compression model [C.S. Burrus, R.A.Gopinath and H.Guo , Introduction to Wavelets and Wavelet Transforms, Prentice Hall, 1998.]

In Huffman entropy coding, the idea is to use two or three numbers for coding, with the first being a signal that a large number or long zero sequence is coming. Entropy coding is designed so that the numbers that are expected to appear the most often in q, need the least amount of space in e.

3.2 Quantization

The fourth step of the process, known as quantization, converts a sequence of floating numbers w' to a sequence of integers q. The simplest form is to round to the nearest integer. Another option is to multiply each number in w' by a constant k, and then round to the nearest integer. Quantization is called lossy because it introduces error into the process, since the conversion of w' to q is not a one-to-one function.

4. 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 the ratio of no. of bits in original image to the no. of bits in 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 with a higher value indicating less distortion.

5. EXPERIMENT RESULTS & DISCUSSIONS

We also are presenting compression results of test images in terms of visual quality for different wavelet functions for wavelet Families. This analysis presents an analysis of Image Compression using DWT. In Image Compression using DWT various wavelet families are used for compressing

5.1 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 compression on test image Cell (159X191). Results are measured in terms of Signal to Noise Ratio (SNR), Compression Ratio (CR) and visual quality of compressed image. The comparison of CR & PSNR values of wavelets of each wavelet family is shown in figure3. Figure 4, 5 ,6 show graphs between the Compression Ratio & wavelets used of the cell image for db, bior, coif wavelet families respectively. Similarly Figure 7, 8, 9 show graphs between time of execution & wavelet used for cell image for db ,bior, coif wavelet families respectively. The tables show the different values of CR, PSNR, SNR, time for execution for biorthogonal , Coiflets & Daubechies Wavelet families for cell 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. Results obtained with the simulation are shown in Fig(10.1) shows recons image using WBC. Fig(10.2) shows difference image.

5.2 Experimental Results

Results obtained with the matlab code are shown below. Fig10.1 shows recons image using WBC. Fig10.2 shows difference image.

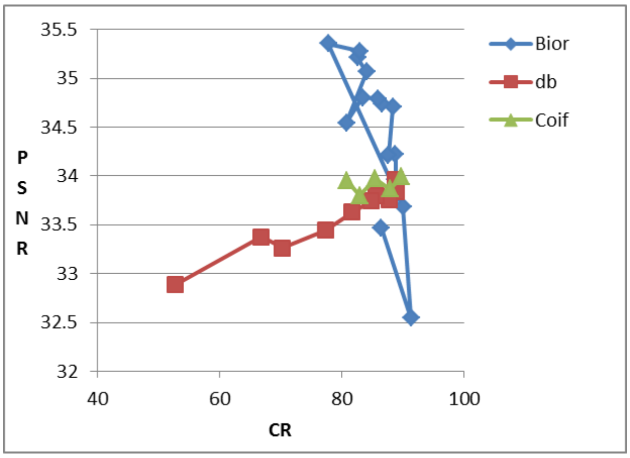

Fig. 3 Graph of PSNR vs. CR

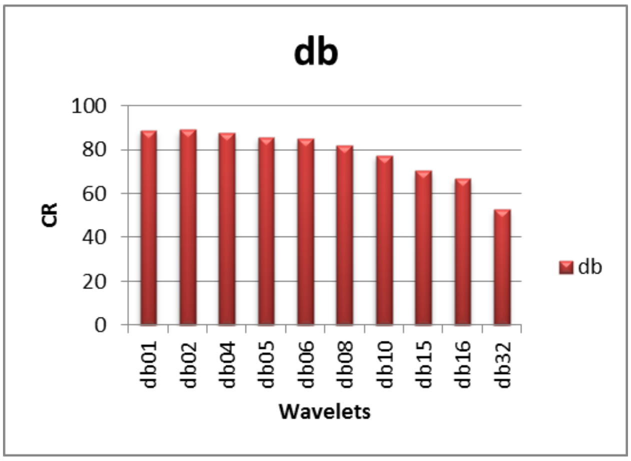

Fig. 4 Graph of CR Vs. db wavelet

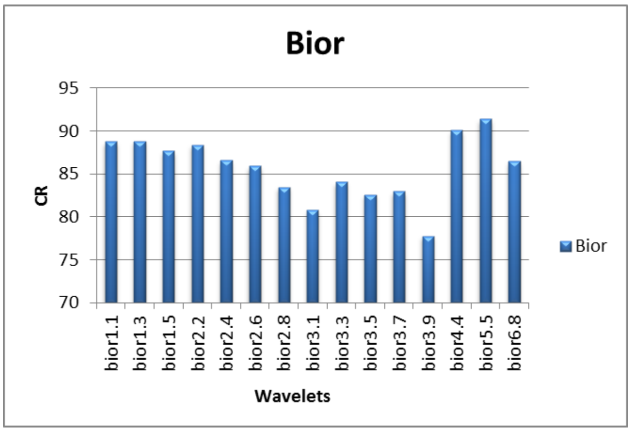

Fig. 5 Graph of CR Vs. Bior wavelet

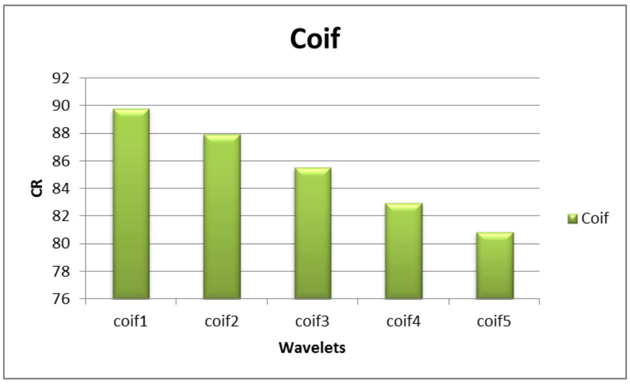

Fig. 6 Graph of CR Vs. Coif wavelet

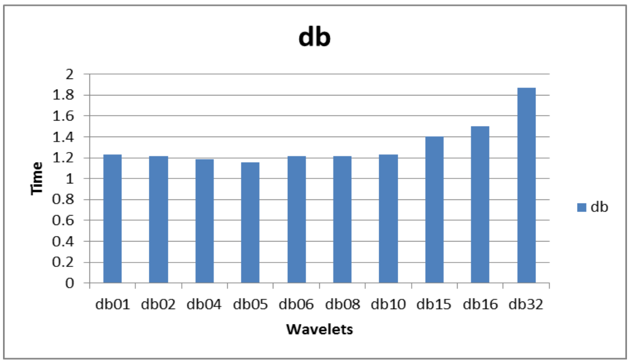

Fig.7 Graph of time vs. db wavelet

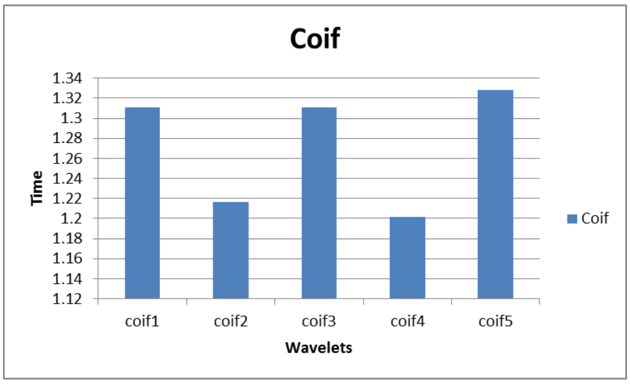

Fig. 8 Graph of time vs. Coif wavelet

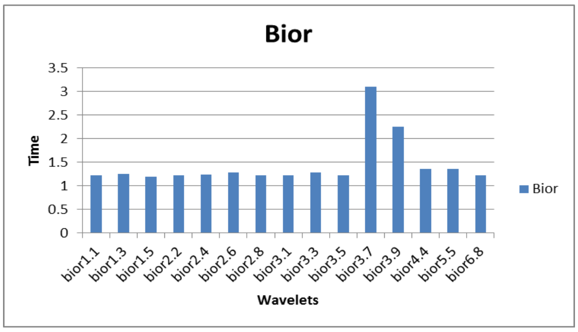

Fig. 9 Graph of time vs. Bior wavelet

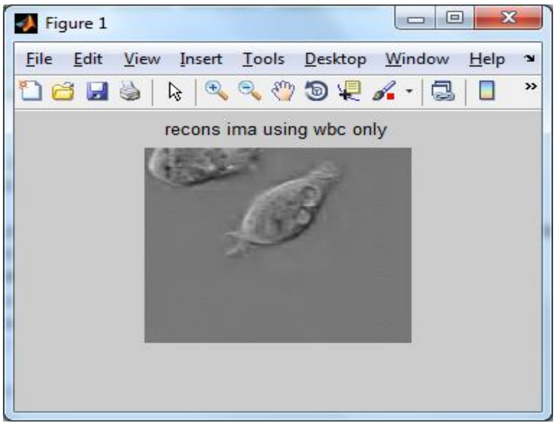

Fig.10.1 recons image using wbc only

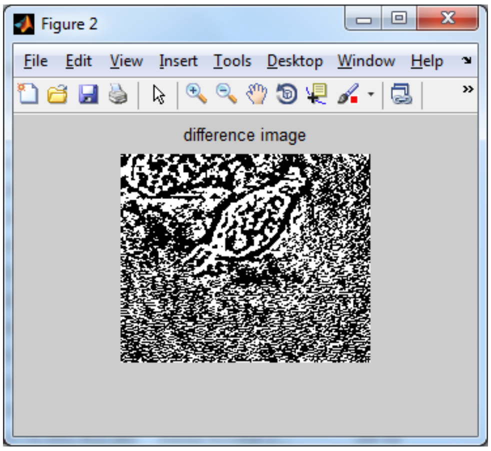

Fig. 10.2 difference image

Tables Showing value CR, PSNR, SNR & Time using different wavelet families

Table1. for Bior

wavelet	CR	PSNR	SNR	Time
bior1.1	88.7588	33.966	5.7078	1.2168
bior1.3	88.8215	34.2166	5.4573	1.248
bior1.5	87.675	34.2128	5.4611	1.1856
bior2.2	88.3489	34.7073	4.9665	1.2168
bior2.4	86.5733	34.7433	4.9306	1.2324
bior2.6	85.9404	34.7922	4.8817	1.2792
bior2.8	83.4448	34.8033	4.8706	1.2168
bior3.1	80.7806	34.5443	5.1296	1.2168
bior3.3	84.069	35.0678	4.606	1.2792
bior3.5	82.602	35.2102	4.4637	1.2168
bior3.7	82.9576	35.2765	4.3974	3.1044
bior3.9	77.7927	35.3551	4.3188	2.2464
bior4.4	90.0439	33.6816	5.9923	1.3572
bior5.5	91.3779	32.545	7.1288	1.3572
bior6.8	86.4629	33.4629	5.7729	1.2168

Table2. for db

wavelet	CR	PSNR	SNR	Time
db01	88.7588	33.966	5.7078	1.2324
db02	88.9964	33.8376	5.8362	1.2168
db04	87.7697	33.7555	5.9183	1.1856
db05	85.6539	33.8015	5.8724	1.1544
db06	84.763	33.743	5.9309	1.2168
db08	81.7179	33.6307	6.0432	1.2168
db10	77.3059	33.4453	6.2286	1.2324
db15	70.2901	33.2628	6.411	1.404
db16	66.8467	33.378	6.2958	1.4976
db32	52.686	32.8877	6.7862	1.872

Table3. for coif

wavelet	CR	PSNR	SNR	Time
coif1	89.77	33.9897	5.6842	1.3104
coif2	87.9276	33.8672	5.8066	1.2166
coif3	85.5066	33.9706	5.7033	1.3104
coif4	82.944	33.7996	5.8743	1.2012
coif5	80.8486	33.9507	5.7231	1.328

6. CONCLUSION

This study presented an analysis of Image Compression using DWT. In Image Compression using DWT various wavelet families are used for compressing image . DWT is used as basis for transformation in JPEG 2000 standard. DWT provides high quality compression at low bit rates. Wavelet analysis is very powerful and extremely useful for compressing data such as images. Its power comes from its multiresolution. Although other transforms have been used, for example the DCT was used for the JPEG format to compress images, wavelet analysis can be seen to be far superior, and in that it doesn't create 'blocking artefacts'. This is because the wavelet analysis is done on the entire image rather than sections at a time. A well-known application of wavelet analysis is the compression of fingerprint. 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 the test image Cell (159X191).The Compression results are measured in terms of CR, PSNR, SNR, time for execution. The Experimental results are discussed here.

In case of Cell image having less pixel size(159X191) bior_5.5, Coi_1 & Db_2 provides the better compression ratio, & SNR. However, bior_5.5 is most efficient wavelet family for compressing low resolution images. With Coi_1, compression ratio is higher but SNR is less compared to bior_5.5. 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.

Finally, it can concluded that for low pixel size image biorthogonal wavelet is best among all the families. 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), 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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