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Compression Effect on Images using different Wavelet Transformation

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***Abstract*-Wavelet transforms are specially used for compression, Denoising, Thresholding, Error reduction, reconstruction, and for image synthesis. There are different types of wavelets are used for image and data compression. Each level has different compression ratio and bits per pixel (BPP) information. If we select a particular level then Mean Square Error (MSE) as well as Peak Signal to Noise Ratio (PSNR) will change. Huffman coding can be used for the quantization depending on the method. More sophisticated methods are available which combine wavelet decomposition and quantization. On one hand, progressivity makes it possible during decoding to obtain an image whose resolution increases gradually. In addition, it is possible to obtain a set of compression ratios based on the length of the preserved code. This compression usually involves a loss of information, but this kind of algorithm enables also lossless compression. Such methods are based on wavelet decomposition, encoding methods, and decision for the use of wavelet for image compression. We are using EZW, SPIHT, STW, WDR, ASWDR, SPIHT_3D, LVL_MMC, GBL_MMC_F, and GBL_MMC_H compression methods to find the MSE, PSNR, Compression ratio (CR) and BPP. The challenge of compression methods is to find the best compromise between a low compression ratio and a good perceptual result.**

***Index Terms*—Compression, Image, Wavelet Transform, Wavelet, PSNR, MSE, CR, BPP, Reconstruction, Synthesis, Decomposition**

I INTRODUCTION

The objective of image compression is to reduce irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form.
Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings & clip art. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences may be called visually lossless.

Images are very important documents nowadays; to work with them in some applications they need to be compressed, 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.

The main focus of this paper is to obtain PSNR, MSE, CR and BPP valve using a particular type of wavelet transform which give lowest MSE, highest PSNR, low CR and low BPP.There are different types of wavelet families whose qualities vary according to several criteria. These types are Haar wavelet, Daubechies wavelet, symlets, coiflets, Biorthogonal wavelet, Reverse Biorthogonal wavelet, discrete approximation of meyer wavelet. At this point I used Daubechies wavelet transform which provides superior result which we need.

II COMPRESSION METHODS

A. HAAR WAVELET TRANSFORM

The Haar Wavelet is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family shown in Figure 1.

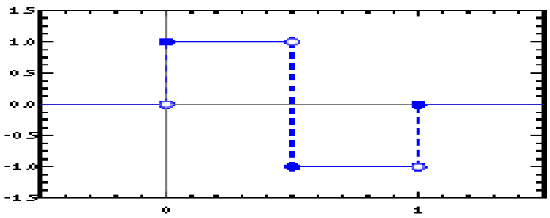

FIGURE 1: HAAR WAVELET TRANSFORM

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The Haar wavelet's mother wavelet function $\psi(t)$ & its scaling function $\phi(t)$ can be described as

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

B. SYMLETS WAVELET TRANSFORM

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. Here are the wavelet functions psis shown in Figure 2.

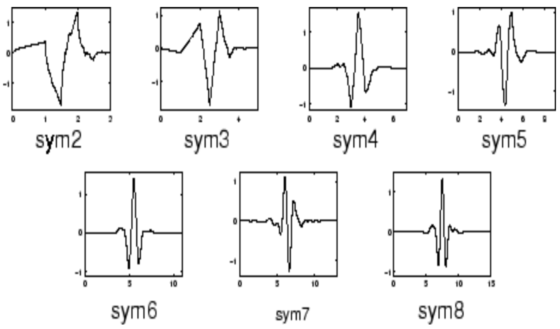

FIGURE 2: SYMLETS WAVELET TRANSFORM

C. DAUBECHIES WAVELET TRANSFORM

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 are the wavelet functions psis of the next nine members of the family shown in Figure 3.

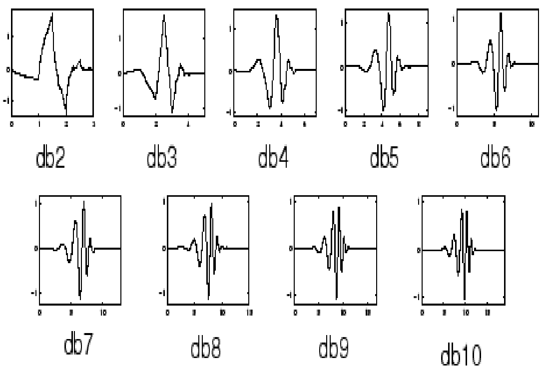

FIGURE 3: DAUBECHIES WAVELET TRANSFORM

D.BIORTHOGONAL WAVELET TRANSFORM

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 which is shown in Figure 4.

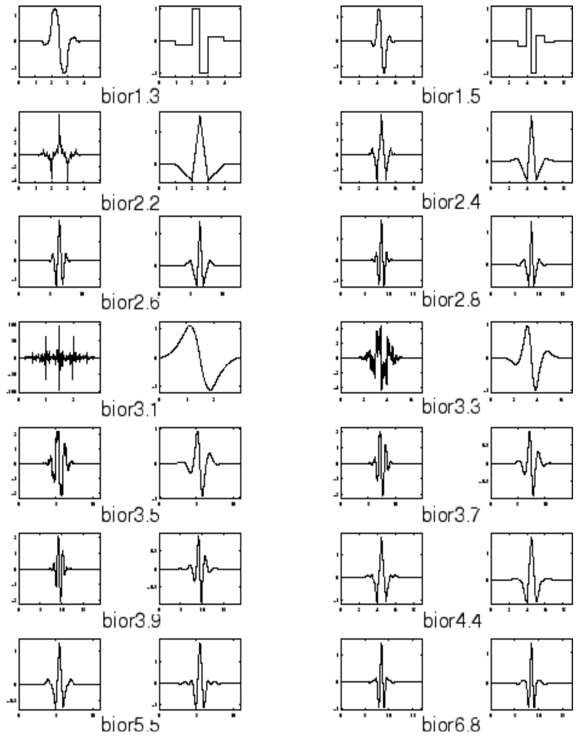

FIGURE 4: BIORTHOGONAL WAVELET TRANSFORM

F. COIFLETS WAVELET TRANSFORM

Built by I. Daubechies at the request of R. Coifman. 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, shown in Figure 5.

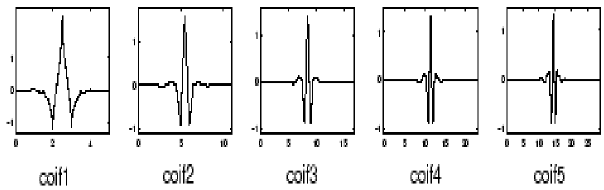

FIGURE 5: COIFLETS WAVELET TRANSFORM

G. MEYER WAVELET TRANSFORM

The Meyer wavelet and scaling function are defined in the frequency domain which is shown in Figure 6.

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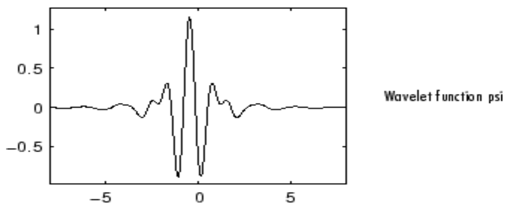

FIGURE 6: MEYER WAVELET TRANSFORM

III RESULTS

Table 1 shows Compression ratio of Db & Symlets WT and their comparison represent graphically in figure 7.

Level	Compression ratio in %	
	Db WT	Symlets WT
1	117.16	105.41
2	57.23	54.66
3	30.52	28.9
4	15.46	14.31
5	5.81	5.52
6	5.57	5.22
7	1.86	1.93

TABLE 1: COMPRESSION RATIO OF DB & SYMLETS WT

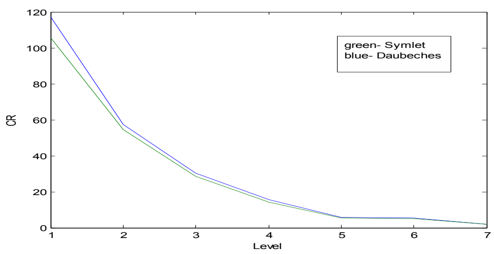

FIGURE 7: COMPARISON BETWEEN CR OF DB & SYMLETS WT

Table 2 shows BPP of Db & Symlets WT and their comparison represent graphically in figure 8.

Level	BPP	
	Db WT	Symlets WT
1	9.3726	9.2324
2	4.5786	4.3726
3	2.4414	2.2954
4	1.2368	1.145
5	0.46484	0.44189
6	0.44531	0.41797
7	0.14894	0.1543

TABLE 2: BPP OF DB & SYMLETS WT

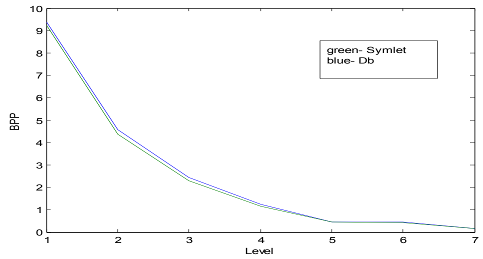

FIGURE 8:COMPARISON BETWEEN BPP OF DB & SYMLETS WT

Table 3 shows Mean square error(MSE) of Db & Symlets WT and their comparison represent graphically in figure 9.

Level	MSE	
	Db WT	Symlets WT
1	0.01672	0.02401
2	0.1716	0.2117
3	1.254	1.439
4	7.699	8.52
5	33.56	33.23
6	172.5	118.7
7	128.1	118.7

TABLE 3: MSE OF DB & SYMLETS WT

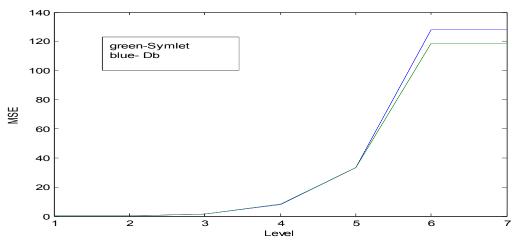

FIGURE 9: COMPARISON BETWEEN MSE OF DB & SYMLETS WT

Table 1 shows Peak signal to noise ratio of Db & Symlets WT and their comparison represent graphically in figure 10.

Level	PSNR	
	Db WT	Symlets WT
1	65.9	64.33
2	55.78	54.87
3	47.15	46.55
4	39.27	38.83
5	32.87	32.92
6	27.06	27.39
7	27.06	27.39

TABLE 4: PSNR OF DB & SYMLETS WT

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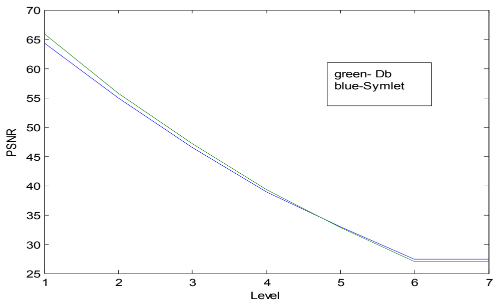

FIGURE 10: COMPARISON BETWEEN PSNR OF DB & SYMLETS WT

Figure 11 shows original image, Fig 12 shows compressed image at level 1 which gives minimum MSE & maximum PSNR in Db WT and Fig 13 shows compressed image at level 7 which gives minimum CR & minimum BPP in Db WT.

FIGURE 11: ORIGINAL IMAGE

FIGURE 12: COMPRESSED IMAGE AT LEVEL 1 WHICH GIVES MINIMUM MSE & MAXIMUM PSNR

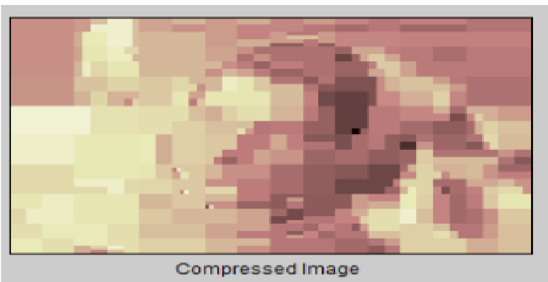

FIGURE 13: COMPRESSED IMAGE AT LEVEL 7 WHICH GIVES MINIMUM CR & MINIMUM BPP

IV.CONCLUSION

By working on different methods of wavelet families we observe Daubechies (Db) Wavelet Transform is best because it gives the superior values of MSE, PSNR, CR and BPP results. We obtain minimum MSE, high PSNR at level 1 of EZW (Embedded Zero tree of Wavelet Coefficient) and minimum CR, minimum BPP at level 7 of SPIHT_3d (Set Partitioning in Hierarchical Trees_3d).

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