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Comparison of Wavelet Based Image Compression on Medical Images

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Abstract

This paper compares the different wavelets based image compression on different medical images. In this paper, firstly different types of wavelets of same family are compared with each other on the same image to get the best wavelet from the family. Then these wavelets are compared for the different images. The comparison shows that the Biorthogonal6.8 has the best compression score for few images. The analysis shows the different wavelet shows different results for the compression on different images. It means the use of wavelet for image compression depends upon the image selection.

Keywords: *Symlets, Discrete Meyer, Biorthogonal, Wavelet, Image Compression.*

I. Introduction

Image compression is needed to reduce the computer memory space and minimization of transmission expenditure [1]. The minimization in folder volume permits greater pictures to be saved in presumption volume of diskette or volume of memory. It decreases the time needed for pictures to be directed above the net or downloaded through Web pages. There are a number of methods by which files of image can be compressed. Image compression could be lossy or lossless. Lossless compression is favoured for archival objects and generally for technical drawings, medical imaging, or comics, clip art. This is because lossy compression schemes specifically when utilized at lowest point of bit rates, establish compression artifacts. Lossy techniques are specially appropriate for natural images like photographs in programs wherever minor loss of precision is allowable to obtain a significant minimization in bit rate. The lossy compression which generates imperceptible dissimilarities could be labeled as visually lossless [2].

Even though the price of storage in computer memory is dropping abruptly as the volume for each instrument rises, or the worth of broadcast bandwidth is as well declining; there continues a determined request for remedial figure compaction. For change over nets with maximum bandwidth, or used for storing on electromechanical machines, substantial period can be exhausted on compression in advance it develops into a aspect in the whole transfer time [3].

The price of implementing compaction should exist accompanied into sketch. Difficult compaction systems are very expensive to evolve, perform, utilize. The usage of uncommon programs has a price, and uncertainty is connected through the termination of existence of an apparatus. It could also determine interoperability using different apparatus. The utilization of industry-wide principles can decrease the price and uncertainty of implementing of compression. The utilization of consumer industry principles is much better [3].

Medical images such as CT scan is a unique image needs lossless compression like a minor loss can lead to unfavorable effects [1]. For high compression, a Prediction method is used. Therefore, to estimate value of present data from existing data [4]. A great number of image data is created for medical imaging, computed tomography scan, positron emission tomography, magnetic resonance imaging, and ultrasound images that may be saved n picture archiving and hospital information system or communication system. A mid-point clinic accompanied by the previously described works produces a standard out of 5–15 GB of every day. Therefore, it is too hard for clinics to maintain the stocking prerequisites for all above. Even though, that high range of data requires an overhead network, mainly for conveying the portraits on the web like in telemedicine. It is a genuine representative the restrictions of the communication broadcast in data and transmission technology, particularly for rustic areas [5].

The paper is organized in the following way. Section II deals with the performance measure parameters. Concept of Wavelet is described in section III.A discussion of performance measures of different algorithms is presented in section IV and then results are discussed in section V.

II. Performance Measure

There are several methods that can evaluate and compare different compression algorithms. For measuring the error among images, two measures are generally used. These are MSE and PSNR. PSNR is implemented generally, It is a logarithmic quantity, and human intelligence appear to answer logarithmically to intensity. Growing PSNR means enlarging precision of compression. Commonly when the PSNR is larger than or equivalent to 40 dB, it is expressed that the two images are effectively indistinguishable by human viewers [6].

III. Wavelets

A wavelet is a fluctuation that has all the properties of a wave. It allows to analyze the time as well as the frequency domain at the same time [7]. The basic purpose of the wavelet theory is to analyze the signal by using simple functions. The scaling function is used to get the various components of the signals [8]. The main application of the wavelet is to reconstruct the signal by using the coefficients of the wavelet. It is also useful in pattern recognition. The perfect reconstruction of the signal is possible by using the two orthogonal waves, one for analysis and other for the synthesis purpose[8].

IV. Wavelet Based Coding Schemes

This sections gives brief of various existing wavelet based compression techniques. These techniques are compared in the next section on different images by using MATLAB.

(i) Daubechies Wavelets

Daubechies Wavelets are basically orthogonal waveletsand used to analyze the different wavelets. The wavelets in the Daubechies Wavelets are named as dbN where N is the order of the wavelet. The N depends upon the vanishing points. The width is generally double of the order; following figure shows the different members of the Daubechies family. The wavelet db1, is similar to the Haar wavelet so this paper evaluates the db1 instaed of the Haar wavelet [11]

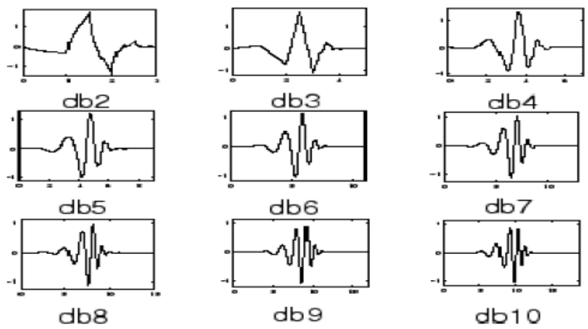

Figure1: Daubechies Wavelet Families[11]

(ii) Coiflet Wavelts

Coiflets wavelets have similar properties as the Daubechies family wavelets. The only exception is that the Coiflet is designed using the vanishing moments for the scaling as well as for wavelet function [10]. The main characteristic of the Coiflets, is their near symmetric; and the vanishing moments in wavelet functions are N/3 while N/3 – 1 in scaling functions. The normalized Coiflets parameters show a good approximation for the polynomial function [11]. This family is useful due to its linear phase but the frequency can't be analyzed easily [10].

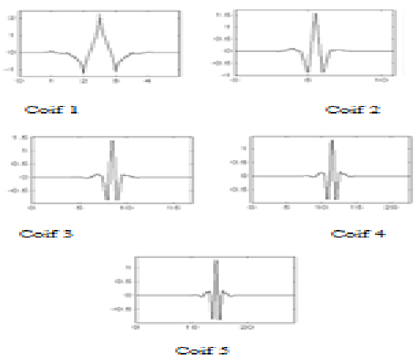

Figure2: Wavelet Functions Of Coiflets[10]

The main feature of this family is its computational efficiency.

(iii) Discrete Meyer Wavelet

The Discrete Meyer i.e. dmey Wavelet is derived the Meyer wavelets by applying the FIR filters. The figure shows the scaling and the wavelet function for dmey. The main characteristic of this family is their orthoganality and the symmetry. The wavelet functions are given in Eq. 1 and scaling functions in Eq.2 [12]:

$\hat{\psi}(\omega) = (2\pi)^{\frac{1}{2}} e^{\frac{i\omega}{2}} sin\left(\frac{\pi}{2} v(\frac{3}{2\pi}|\omega| - 1|)\right) if \frac{2\pi}{3} < |\omega| < \frac{4\pi}{3}$ $\hat{\psi}(\omega) = (2\pi)^{\frac{1}{2}} e^{\frac{i\omega}{2}} cos\left(\frac{\pi}{2} v(\frac{3}{2\pi}|\omega| - 1|)\right) if \frac{4\pi}{3} < |\omega| < \frac{8\pi}{3}$

$\hat{\psi}(\omega) = 0 if |\omega| not\ bleongs\ to [\frac{2\pi}{3}, \frac{8\pi}{3}]$ (1)

Where:

$$v(a) = a^4(35 - 84a + 70a^2 - 20a^3) a \in [0,1]$$

And $\hat{\emptyset}(\omega) = (2\pi)^{-\frac{1}{2}} if |\omega| < \frac{2\pi}{3}$ $\hat{\emptyset}(\omega) = (2\pi)^{-\frac{1}{2}} cos\left(\frac{\pi}{2} v(\frac{\pi}{2}|\omega| - 1|)\right) if \frac{2\pi}{3} < |\omega| < \frac{4\pi}{3})$ $\hat{\emptyset}(\omega) = 0\ if |\omega| < \frac{4\pi}{3}$ (2)

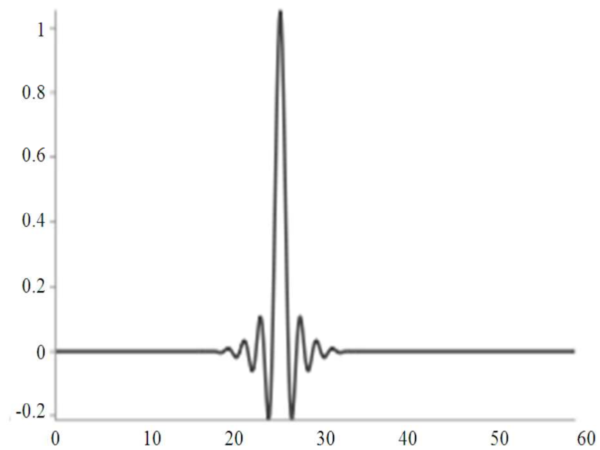

Figure 3: Dmey Scaling Function Φ[12]

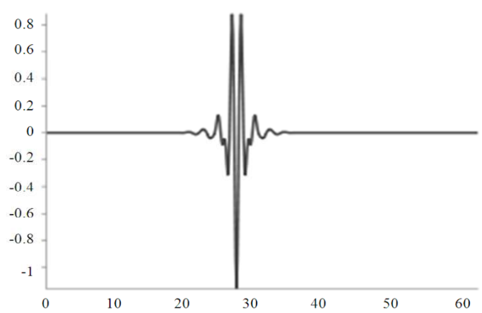

Figure 4: Wavelet function ψ [12]

(iv) Biorthogonal Wavelets

Biorthogonal wavelets expand the class of orthogonal wavelets and comprise programs in image processing. The periodical biorthogonal wavelet transforms are achieved through Matrix-vector outcomes via sparse, structured matrices [11, 13]. An available detail in filter philosophy association is that

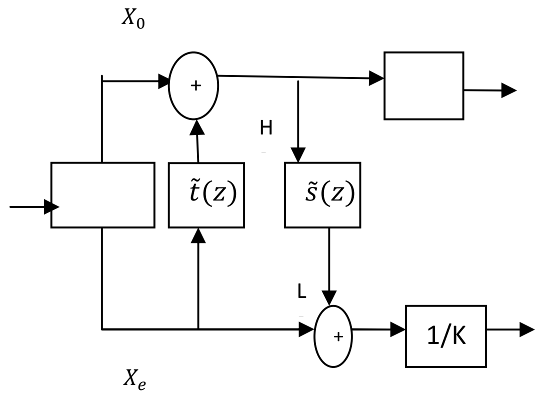

Figure 5: Lifting Schemes. [16]

whenever identical FIR filters are utilized for separation and Reconstruction Period procedure, the symmetry and complete reconstructions are fully inconsistent. To avoid this problem, double scaling and wavelet functions with following properties are implemented [10]:

i) They are zero outward division and computation algorithms preserved are easy.
ii) Filters connected are symmetrical.
iii) Functions utilized for computations are very easy to construct as compared to those which are implemented in Daubechies wavelets.

(v) Symlets

In sym N, N is the order. 2N is used at some places instead of N by the investigators. Daubechies proposed different wavelet like symmetrical, orthogonal as the modified wavelet in the db family. There are similarities by using their properties: [14].

Benefits

1) Symlets come to known as the “symmetrical wavelets”.
2) They are calculated in such a way they have the slightest asymmetry and greatest amount of vanishing moments for a certain compact sustain.

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Drawbacks

1) These are not completely symmetrical

(vi) Lifting Scheme

The wavelet Lifting system is a technique for breaking up wavelet transfigures into a group of phases. Lifting design algorithms have the benefit that they do not need temporal arrays in the computations stages and have fewer computations [15]. Three stages in lifting system

a) Split step

It is also named as lazy wavelet transform. It separates the input data into two parts: odd and even

b) Predict step

This phase forecasts the odd parts from the even parts.

c) Update step

This substitutes the even parts accompanied by an average..

The primary rule of the lifting scheme is to factorize the poly step matrix of a wavelet filter into a series of interchanging higher and lesser triangle-shaped matrices and a diagonal matrix [15], [17]. This directs to the wavelet execution by banded-matrix multiplications. Consider, g(z) and h(z) are the lowest level pass and high up pass evaluation filters, and assume g (z) and h (z) are the lowest level u pass and high up pass synthesis filters. The equivalent poly step matrices are explained as[16]

$$\widetilde{P_1}(z) = \begin{bmatrix} K & 0 \\ 0 & \frac{1}{K} \end{bmatrix} \prod_{i=1}^{m} \begin{bmatrix} 1 & s_1(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_1(z) & 1 \end{bmatrix} \quad (1)$$

$$\widetilde{P_2}(z) = \begin{bmatrix} K & 0 \\ 0 & \frac{1}{K} \end{bmatrix} \prod_{i=1}^{m} \begin{bmatrix} 1 & 0 \\ t_1(z) & 1 \end{bmatrix} \begin{bmatrix} 1 & s_1(z) \\ 0 & 1 \end{bmatrix} \quad (2)$$

Here k is a stable, ti(z) and si(z) are represented as main lifting and double lifting polynomial correspondingly and m denotes the complete lifting phases needed. The two kinds of lifting schemes are presented in Figure 5 [16].

V. Results

The comparison of image compression on various images is done by using the various parameters i.e. compression score and the PSNR and MSE. The compression score describe that how much the image is compressed. The target is to get the greater compression with good image quality. The PSNR is inversely proportional to the MSE and it describes the image quality. Different images used for analysis are shown in figure 6.

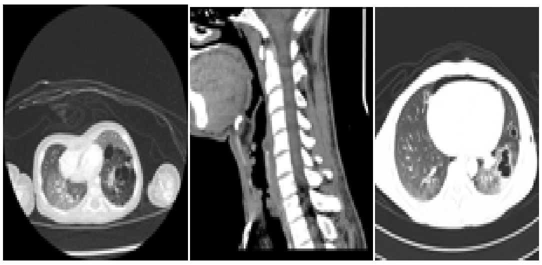

Figure 6: jpg, 4.jpg, 5.jpg

The table 1 shows the comparison of the wavelet functions of the symlets family on the 3.jpg.

Table 1: Comparison of Different Wavelets of Symlets Family

Compression Type	Image Name	PSNR	MSE	Compression Score
Symlets2	3.jpg	52.9226	0.6580	49.3987
Symlets4	3.jpg	52.7124	0.6877	51.2982
Symlets8	3.jpg	52.7569	0.6826	52.2751
Symlets10	3.jpg	52.8317	0.6748	52.9666

The comparison table shows that the symlets10 has the best compression score along with the PSNR and the MSE value. In other words the Symlets10 has highest compression score with good PSNR and less MSE. The table 2 shows the comparison of the wavelet functions of the Daubechies family on the 3.jpg

Table2: **Comparison of Different Wavelets of Daubechies Family**

Compression Type	Image Name	PSNR	MSE	Compression Score
Daubechies1	3.jpg	53.7547	0.5780	47.6986
Daubechies 2	3.jpg	52.9226	0.6580	49.3987
Daubechies 4	3.jpg	52.8182	0.6765	51.0465
Daubechies 8	3.jpg	52.8256	0.6720	51.5845
Daubechies 10	3.jpg	52.8319	0.6733	52.1765
Daubechies 45	3.jpg	53.7671	0.5464	42.0342

The comparison table shows that the Daubechies10 has the best compression score along with the PSNR

Table 3 Comparison of Different Wavelets of Coiflets Family

Compression Type	Image Name	PSNR	MSE	Compression Score
Symlets10	3.jpg	52.8317	0.6748	52.9666
Symlets10	4.jpg	50.8299	1.0558	81.2713
Symlets10	5.jpg	49.8640	1.4279	62.2683

and the MSE value. In other words the Daubechies 10 has highest compression score with good PSNR and less MSE. The table 3 shows the comparison of the wavelet functions of the Coiflets family on the 3.jpg .

Table 4 Comparison of Different Wavelets of Biorthogonal Family

Compression Type	Image Name	PSNR	MSE	Compression Score
Coiflets1	3.jpg	52.8886	0.6613	49.8239
Coiflets2	3.jpg	52.8061	0.6789	51.4510
Coiflets3	3.jpg	52.8450	0.6718	52.4818
Coiflets4	3.jpg	52.8079	0.6787	53.5871
Coiflets5	3.jpg	52.7820	0.6800	54.2946

The comparison table shows that the Coiflets5 has the best compression score along with the PSNR and the MSE value. In other words the Coiflets 5 has highest compression score with good PSNR and less MSE. The table 4 shows the comparison of the wavelet functions of the Bioorthogonal family on the 3.jpg

The comparison table shows that the Biorthogonal6.8 has the best compression score along with the PSNR and the MSE value. In other words the Biorthogonal6.8 has highest compression score with good PSNR and less MSE. The best wavelets selected from the above defined wavelet families are compared with each other. Two more techniques i.e. Discrete Meyer wavelet based image compression and the lifting transform image compression is also compared on the image 3.jpg. The table 5 shows the comparison of different wavelets on same image by using the PSNR and MSE and the compression score.
This comparison shows that the Discrete Meyer has the best compression score i.e. 55.5871 which s better than all other and PSNR of same technique is highest among all other wavelets. The MSE is minimum for this technique so the Discrete Meyer wavelet based image compression shows best results for the 3.jpg.
The table 6 shows the symlets 10 performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score on the image 4.jpg is highest than the 5. Jpg and least for 3.jpg.

Table 5 Comparison of different wavelet based compression on 3.jpg

Compression Type	Image Name	PSNR	MSE	Compression Score
Biorthogonal1.1	3.jpg	53.7547	0.5780	47.6986
Biorthogonal 2.8	3.jpg	51.0732	0.9953	51.8637
Biorthogonal 3.9	3.jpg	48.2524	1.9132	52.8291
Biorthogonal 4.4	3.jpg	52.6676	0.6991	50.8901
Biorthogonal 5.5	3.jpg	52.8030	0.6805	50.1692
Biorthogonal6.8	3.jpg	52.5553	0.7152	52.8498

Table 6 Symlets10 based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compression Score
Biorthogonal6.8	3.jpg	52.5553	0.7152	52.8498
Biorthogonal6.8	4.jpg	50.7975	1.0584	82.0751
Biorthogonal6.8	5.jpg	49.8885	1.4261	62.8548

Table 7 Daubechies10 based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compr ession Score
Symlets10	3.jpg	52.8317	0.6748	52.966 6
Daubechies 10	3.jpg	52.8319	0.6733	52.176 5
Coiflets5	3.jpg	52.7820	0.6800	54.294 6
Biorthogonal6.8	3.jpg	52.5553	0.7152	52.849 8
Discrete Meyer	3.jpg	52.9595	0.6490	55.587 1
Lifting Transform	3.jpg	34.5706	94.4799	50.000 0

The table 7 shows the Daubechies 10 performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score on the image 4.jpg is highest than the 5. Jpg and least for 3.jpg.

Table 8 Coiflets5 based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compression Score
Daubechies 10	3.jpg	52.8319	0.6733	52.1765
Daubechies 10	4.jpg	50.4830	1.1372	79.7509
Daubechies 10	5.jpg	49.7004	1.4775	61.1157

The table 8 shows the Coiflets 5 performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score on the image 4.jpg is highest than the 5. Jpg and least for 3.jpg.

Table 9 Biorthogonal6.8 based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compression Score
Coiflets5	3.jpg	52.7820	0.6800	54.2946
Coiflets5	4.jpg	50.7913	1.0660	81.0722
Coiflets5	5.jpg	49.9654	1.4007	60.4470

The table 9 shows the Biorthogonal6.8 performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score on the image 4.jpg is highest than the 5. Jpg and least for 3.jpg.

Table 10 Discrete Meyer based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compression Score
Discrete Meyer	3.jpg	52.9595	0.6490	55.5871
Discrete Meyer	4.jpg	50.4753	1.1393	75.3964
Discrete Meyer	5.jpg	49.7214	1.4613	58.5219

The table 10 shows the Discrete Meyer performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score on the image 4.jpg is highest than the 5. Jpg and least for 3.jpg.

Table 11 Lifting Transform based Image Compression on Different Images

Compression Type	Image Name	PSNR	MSE	Compression Score
Lifting Transform	3.jpg	34.5706	94.4799	50.0000
Lifting Transform	4.jpg	37.0023	70.7130	50.0000
Lifting Transform	5.jpg	36.1326	103.4776	50.0000

The table 11 shows the Lifting transform performances on different images i.e. 3.jpg, 4jpg and 5.jpg. The compression score is same for all images.

The graphical comparison of different images on different wavelet is shown from figure 6.8 to figure 6.10. These figures compare the PSNR and MSE and the Compression ratio respectively.

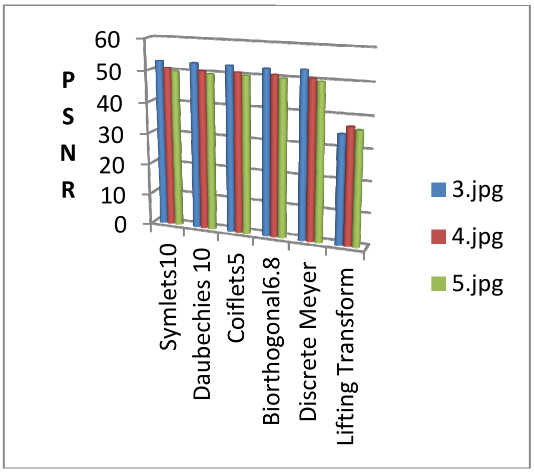

Figure 7Comparison of PSNR for different images

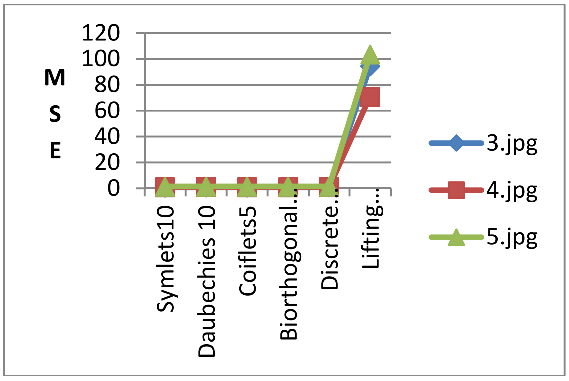

Figure 8 Comparison of MSE for different images

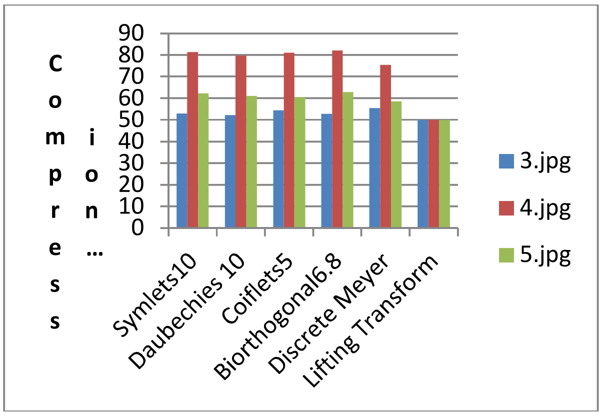

Figure 9 Comparison of Compression Score for different images

The comparison and analysis of these graphs shows that the Biorthogonal6.8 has the best compression score for the 4.jpg i.e. 82.0751 while the discrete Meyer has for 3.jpg i.e. 55.5871. The analysis shows the different wavelet shows different results for the compression on different images. It means the use of wavelet for image compression depends upon the image selection. The increase in the PSNR and compression ratio correspondingly decrease in the MSE is same in all wavelets i.e. if compression ratio of one image is greater as compared to other in one wavelet than it will be greater in other wavelet also. The difference between the compression score may vary depending upon the type of wavelet used. The lifting transform shows the worst results as the MSE of lifting transform is very much higher as compared to others. But the compression ratio remains same for all images in lifting transform and the compression ratio can be enhanced in a larger amount with small increase in the MSE.

VI. Conclusion and Future Scope

In this paper, the comparison is done between the different wavelets of the Symlets, Daubechies, Coiflets and Biorthogonal families and the Symlets10, Daubechies10, Coiflets5 and Biorthogonal6.8 are found to be better than the other wavelets of the same family respectively. Then these wavelets are compared for the different images. In addition to these the Discrete Meyer wavelet and lifting transform based compression is also compared on different images. The comparison shows that the Biorthogonal6.8 has the best compression score for the 4.jpg i.e. 82.0751 while the discrete Meyer has for 3.jpg i.e. 55.5871. The analysis shows the different wavelet shows different results for the compression on different images. The increase in the PSNR and compression ratio correspondingly decrease in the MSE is same in all wavelets. In future, the artificial intelligence can be used to enhance the PSNR and the compression score.

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