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An Efficient Analysis of Wavelet Techniques on Image Compression in MRI Images

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ABSTRACT

Compression can be defined as an art form that involves the representation of information in a reduced form when compared to the original information. Image compression is extremely important in this day and age because of the increased demand for sharing and storing multimedia data. Compression is concerned with removing redundant or superfluous information from a file to reduce the size of the file. The reduction of the file size saves both memory and the time required to transmit and store data. Lossless compression techniques are distinguished from lossy compression techniques, which are distinguished from one another. This paper focuses on the literature studies on various compression techniques and the comparisons between them.

Keywords: *Image processing, MRI images, Compression, Transform.*

1. Introduction

Image compression encoding [1] stores an image in the smallest possible compact bitstream, and image decoding displays the image in the exact or as close to the exact image as possible. Encoding and decoding images are two distinct processes [2]. An encoder receives an image file in any format and converts it to a bitstream. The decoder then receives an encoded bitstream and decodes it. An image is considered compressed when the total data quantity of a bitstream is less than the total data quantity of the original image [3]. The rate at which bits are compressed determines the amount of bandwidth required to transmit video images, as well as the amount of hard disc space required by a network video recorder or digital video recorder. This paper compares the compression ratio (CR), peak signal to noise ratio (PSNR), encoding time (EcT), and decoding time (DcT) of the Haar wavelet, DCT, and Bi-orthogonal wavelet transforms.

Digital images are typically encoded using lossy compression due to the high memory and bandwidth requirements. Lossy compression achieves high compression ratios at the expense of image quality. Various situations necessitate avoiding images used in medical, prepress, scientific, and artistic images due to information loss or compression artifacts [4]. The number of images available on the internet has increased exponentially since the advent of the internet and the multimedia era, increasing the demand for effective image compression techniques. More redundancy in an image data set means more compression, which means a smaller overall file size for the output image [5]. A sophisticated compression algorithm reduces the size of an image. To reconstruct images, invertible or reversible processes are required. In general, invertible properties are achieved by mapping samples of integer inputs to integer output values. Color transformation involves transforming red, green, and blue colour components to decorate them (RGB) [6]. Fractal encoding and fractal pressure are two techniques that use the self-similitude property of fractal items [7]. Squares in a picture are obtained by shading after dividing a picture into 88 comparable pieces to avoid dreary pressure, the fractal picture pressure concept is used on a square of similar size. Quantized picture pieces are used to simulate fractal picture pressure [8]. The area hinders that are coordinated obstruct range in a picture for each obstruct can be recognized using fractal picture pressure. The Euclidean separation is used to compare two images. The time required to decompress an image is called decoding time (DCT), whereas encoding time (ECT) is required to compress an image. It is a measure of a compression system's ability to distinguish between noise and a pictorial signal in a compressed image. If the ratio is too small, the compression system cannot distinguish between noise and a pictorial signal.

There are two main process definitions for two complex processes, compression, and decompression. Compression is defined as transforming an original data representation into a representation of simple bits. Decompression is the reverse of compression and involves reassembling the decompressed data set from the original data set. Visually lossless compression refers to the absence of visible data loss during compression and decompression. The evaluation found that image compression is visually lossless and highly subjective.

2. Literature Survey

The global population's use and reliance on computers grow as technology advances. Images, for example, have limited bandwidth and storage, so they must be compressed before transmission and storage [9]. For example, someone with a large number of images on their website or online catalog will likely need to use an image compression technique to store them because the amount of space required to store inadequate images can be unreasonably large in both cost and size. Images can be compressed using a variety of methods. Image compression is divided into two types: lossless and lossy. Images lose fidelity when compressed, especially at lower bit rates. If the compression ratio is too high [10], the reconstructed images lose quality and some artifacts are lost. DCT is the technique to use when a high compression ratio is required along with a high-quality reconstructed image. A sequence of finite multiple data points can be expressed using the Discrete Cosine Transform expression, which is a sum of cosine functions oscillating at different frequencies. It is widely used because DCT compression is extremely efficient in lossy image compression, which is what JPEG is designed to do. In DCT and Fourier transforms, images are converted into frequency-domain decor relate pixels [11, 12]. DCT has reversibility because it divides images into parts with different frequencies that can be reconstructed. Less important frequencies are eliminated during quantization, resulting in "lossy compression," while the most important frequencies are only retained to retrieve the image during decompression, resulting in "lossless compression." Diffusion causes distortion in some parts of the image reconstruction, but it can be adjusted during compression. The JPEG method supports both grayscale and colour images [13]. The Haar Wavelet Transform is a simple and memory-efficient image compression method. Other features include speed and fundamental transformations from space to local frequency domain [14]. A Haar Wavelet transform decomposes each signal into two components, the average (approximation) or trend component and the difference (detail) or fluctuation component. This includes the size of any arrays created as a result of the conversion.

The Haar wavelet transform divides an image into high and low-frequency components. To produce a compressed image, each of the results from the first cycle is combined with those from the second cycle [15].

According to V. Mishra et al., a bi-orthogonal wavelet transform is an orthogonal wavelet transform that has symmetry in its filter, making it easier to use the filter functions and maintain the computation algorithms [16]. All image data is zero outside of the segment, so any information about the region is lost. The bi-orthogonal wavelet transform generates two different wavelet functions while generating two different scaling functions. According to M. Beladgham, the wavelet transform's symmetry as well as orthogonality make the reconstruction error close to the quantization error, resulting in high image quality even when compressed [17].

According to S. Gupta, the Compression ratio of a lossy image is higher than a lossless image. Discrepancies in the sparse matrix difference between lossless and lossy images cause this [18]. A lossy image with a sparse matrix with more zeros than a lossless one discards more information during the filtering transform, resulting in a smaller image size. Lossy image compression outperforms lossless image compression. Lossy images are difficult to reconstruct due to a large amount of information lost, whereas lossless images are easy to reconstruct due to the small amount of information lost.

3. Proposed System

This system involves the usage of MRI images as input before compression such that the compressed image is stored in a given storage unit (e.g., hard drive), so that space occupied by the compressed images is less than the space occupied by the original images while identifying and maintaining the relevant and essential elements on the image. This system not only does it do that, but it also gives the numerical values from given parameters such as PSNR and CR of different compression techniques in DWT. The block diagram is given in Fig.1.

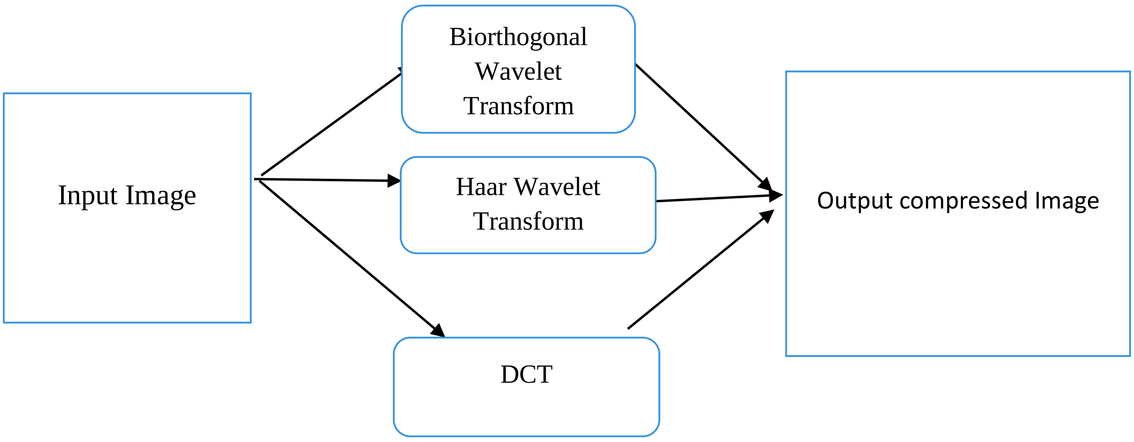

Fig.1. Block Diagram

3.1. Haar Wavelet Compression

It is an efficient lossless and lossy image compression which uses averaging and differencing an image into bands from an image of size N×M to a **nearly sparse matrix** of which a large set of entries is zero which is stored in an efficient manner causing its size to be small. This type compression performs better in grey scale images and since it is applied in MRI images there is a need of the technique to be lossless in order to prevent loss of relevant information.

An image being a matrix it is represented in the formula:

$$B = H^T \times AH \qquad (1)$$

Here, B is the compressed matrix, H is invertible matrix. And A is the original matrix.

From the formula (1) it is shown that B is nearly sparse as compared to A.

Images are represented as piecewise half open coordinate [0, 1] present in a vector space called V^0. When the vector space is V^1 is represented as [0, ½] and [½,1] such that if this is applied recursively until a vector space V^j is reached as the limit such that all these other vector spaces other that V^0 they are subsets of V^0.

During compression a horizontal filter is applied before applying a vertical and diagonal filter consecutively so that a sparse matrix is produced whereby a few coefficients have a value greater than zero and the produced image is compressed by scaling and translation functions which are represented as follows:

(a) LL is low pass filters for both vertical and horizontal.

(b) LH low pass filter for the horizontal and high pass filter for the vertical.

(c) HL high pass filter for the horizontal and low pass filter for the vertical.

(d) HH both vertical and horizontal high pass filter making it a diagonal.

This is called level 1 and level 2 can be applied inside the LL band. The increase in levels increases the extent of compression but if the quality or energy of the compressed image is to be specified the value of a threshold is needed since the zero values of a sparse matrix are traded with the quality of an image.

There are four main stages involved in image compression with Haar wavelet filter.

(1) An original image is represented as the original matrix.

(2) A transformed matrix is produced from the original matrix by application of averaging and differencing.

(3) Using threshold to find the new matrix whose quality is improved.

(4) Using the result of the image produced after the threshold value application to calculate parameters like CR, PSNR and ECT.

3.2. DCT Compression

Discrete cosine transform compression is a technique that is used in the conversion of a signal into an elementary component frequency and it is used commonly in most of the compression done here.

Mentioned earlier on, this project is applied in two-dimensional images (MRI images specifically) hence it uses the matrix of N×M. It involves the application of each row and column with the one-dimension and the transform is given below:

$$S\ u,v = \frac{2}{\sqrt{nm}} C\ u\ C\ v \sum_{y=0}^{m-1} \sum_{x=0}^{n-1} s\ x,y\ \cos\frac{(2x+1)u\pi}{2n} \cos\frac{(2y+1)u\pi}{2m} \qquad u = 0,\ldots,n\ v = 0,\ldots,m \quad (2)$$

Where,

$C\ u\ = 2^{-1/2}\ for\ u = 0$

$C\ v\ =\ 1\quad otherwise$

Some properties of the DCT which are of particular value to image processing applications:

a. Decorrelation: After the separate row or column compression function of DCT has been applied the results are integrated to produce a finished and compressed image. One of the best outcomes using DCT in compression is a high CR (compression ratio). In the reduction of the image either quantization or entropy are used.

b. Energy Compaction: These are some of the features of the DCT that make it a good choice for image processing: The most significant benefit of image transformation is removing redundant information between adjacent pixels. Uncorrelated transform coefficients are generated, allowing them to be encoded separately. Based on the evidence, it can be concluded that DCT has excellent decorrelation properties.

c. Separability: A transformation scheme's efficacy can be directly measured by compressing as much information into as few coefficients as possible. The quantizer can safely discard coefficients with low amplitude when they are encountered to avoid visual distortion. DCT is an excellent energy compaction method when dealing with highly correlated images.

d. Symmetry: The DCT transform equation can be expressed in terms of separability. To take advantage of this property known as separability, D I j) can be computed in two steps by performing successive 1-D operations on the rows and columns of an image. The inverse DCT can be computed using the same logic as presented here. Symmetry is d. As you can see from Equation 1, the row and column operations are functionally identical. It's called asymmetric transformation because it's symmetrical. Separable symmetric transforms can be expressed in terms of an N-symmetric transformation matrix, where M is the symmetric transformation matrix. If the transformation matrix is precomputed offline and then applied to the image, it will result in orders of magnitude more computation efficiency than the standard method. This is an advantageous property.

3.2.1. Comparison of matrix

After decompression and reconstruction of the image blocks, we discarded nearly 70% of the DCT coefficients, so let's see how the JPEG version of our original pixel block compares.

(1) The One-Dimensional DCT: It is a transform that, like others, attempts to decorrelate the image data using the Discrete Cosine Transform (DCT). The compression efficiency of the overall transformation is unaffected by encoding transform coefficients individually. The DCT and some of its most significant features are discussed in detail in this section.

u = 0, 1, 2, and N, the most common DCT definition for 1-D sequences of length N is as follows: Zero, one, and two

(2) The Two-Dimensional DCT: Likewise, the inverse transformation is defined as follows: To get x = 0, 1, 2, n, use the following formula. Because of this, the first transform coefficient is used to represent the sample sequence's mean value. The DC Coefficient is a scientific term for this value. The AC Coefficients refer to all of the other transform coefficients.

In the second dimension, a linear combination of weighted basis functions is created using the DCT. Input data can be transformed into a linear combination of weighted basis functions using various transforms, including the Discrete Cosine Transform (DCT). It's common to use frequency as one of these fundamental functions. If you look at the 2-D Discrete Cosine Transform, you'll see that it's just a 1-D Discrete Cosine Transform that has been applied twice. It's easy to see how computationally challenging it would be to deal with a large image. As a result, many algorithms, such as the Fast Fourier Transform (FFT), have been developed to speed up the computation. An image is calculated using the DCT equation (Eq.1) for an image, which is the DCT equation for an image with p (x,y) as its matrix. The letter N denotes the block size on which the DCT is performed. The pixel values of the original image matrix are used to calculate a single entry (i, jth) of the transformed image matrix.

4. Bi-Orthogonal Wavelet Filtering in Compression

This type of filtering process during compression particularly DWT compression involves the usage of different filtering techniques whose efficiency is different when applied to different images. This paper being specifically applied in MRI images, Bi-orthogonal wavelet filtering works as orthogonal wavelet filter only that it has less energy conservation, does not support asymmetry and regularity as compared to the orthogonal wavelet filter.

Given the nature of the bi-orthogonal filters not conserving energy or not Retaining Energy (RE) hence it is lossy and not lossless. Lossless compression entails that RE percentage is 100%, but in bi-orthogonal filtering RE cannot be 100% due to its inability of supporting asymmetry thus eventually losing all details that are asymmetric resulting in a compressed image with low retained energy. MRI images have a lot of areas with details that are asymmetric and if a tumor which is an area of interest during diagnostics is asymmetric, the retained energy on those regions is very low hence resulting in the loss of important details which can result in mis-diagnosis.

As a general law of thumb, wavelet filtering involves the quantization of wavelet coefficients. These coefficients are classified into approximation coefficients and detail coefficients where by approximation coefficients deals with giving pixel values of an image while detail coefficients deal with the horizontal, vertical and diagonal details which is identical with the changes in the images. Thus, MRI images have a lot of details with small magnitude of values and if the details are small enough to be recognized as zero with respect or as specified by the threshold then RE can be close to 100%. Therefore, when using bi-orthogonal wavelet filtering it is required to set threshold as small as possible so that important details are retained and this is the first possible solution to solving the problem of increasing RE in bi-orthogonal wavelet filter. Another solution is defining the ROI (Region Of Interest) by using sample of data from a dataset from which these data are identified for the purpose of lowering the threshold on those areas so that RE is close to 100% thus RE in all regions other than the ROI have RE less than or not close to 100%. ROI used in MRI images uses 2D dataset which might also involve measuring the length of a particular ROI.

Given the high CR (compression ratio) of bi-orthogonal wavelet filter, it is also important for the best wavelet-bank to be chosen at the same time while having the most favorable decomposition level serving as crucial to the CR. The best or optimal wavelets in bi-orthogonal wavelet filter should have the property of bi-orthogonality (this includes symmetric, supported size and recommended number of vanishing moments) which makes the compressed image to have a large CR. Bi-Orthogonal wavelet filter is a family that has other specific filters under it which include: Daubechies, Symlet and Coiflet filters and they are differentiated by their different orders. The orders in bi-orthogonal wavelet filter involve five orders ranging from 1 to 5 and they might carry different thresholds. Bi-orthogonal wavelet filter normally uses two processes during compression of which the first is smoothing data using approximation coefficients in a scaling function φ and the second is differences in terms of fluctuations present in an image using a function ψ and the processes are shown in the equation below:

$$x_i^{n-1} = \sum_{j=0}^{2^n} x_j^n \varphi_{j-2i} \qquad (3)$$

$$y_i^{n-1} = \sum_{j=0}^{2^n} y_j^n \varphi_{j-2i} \qquad (4)$$

If i = 0, … , the process of both scaling and fluctuation can also be represented as a matrix of either complete rows or columns and below is the representations:

Rows

$$\varphi^n(i,j) = \begin{bmatrix} \ldots.\varphi_j \cdots \\ \ldots\varphi_{j-2} \cdots \\ . \\ . \\ \ldots\varphi_{j-2i} \cdots \\ . \\ . \\ \ldots\varphi_{j+2-2^{n-1}} \cdots \end{bmatrix} \qquad (5)$$

Columns

$$\psi^n(i,j) = \begin{bmatrix} \ldots.\psi_j \cdots \\ \ldots\psi_{j-2} \cdots \\ . \\ . \\ \ldots\psi_{j-2i} \cdots \\ . \\ . \\ \ldots\psi_{j+2-2^{n-1}} \cdots \end{bmatrix} \qquad (6)$$

$$\varphi^n(i,j) = \begin{bmatrix} \vdots & \vdots & & \vdots & & \vdots \\ \varphi_j & \varphi_{j-2} & \cdots & \varphi_{j-2i} & \cdots & \varphi_{j+2-2^{n-1}} \\ \vdots & \vdots & & \vdots & & \vdots \end{bmatrix} \quad (7)$$

$$\psi^n(i,j) = \begin{bmatrix} \vdots & \vdots & & \vdots & & \vdots \\ \psi_j & \psi_{j-2} & \cdots & \psi_{j-2i} & \cdots & \psi_{j+2-2^{n-1}} \\ \vdots & \vdots & & \vdots & & \vdots \end{bmatrix} \quad (8)$$

5. Results and Discussions

Table 1. Comparison of Proposed wavelets with Peak Signal Noise Ratio, Compression Ratio, Mean Square Ratio, ECT and DCT

	PSNR	CR	Mean Square Error	ECT	DCT
Haar Wavelet Compression	33.7087	3.72854	27.6829	1s	4s
Bi-orthogonal Wavelet Compression	34.3987	2.64354	28.1539	1s	3s
DCT Compression	36.3716	26.9807	14.9942	3s	5s

Table 2. Property Comparison of Three kinds of Wavelets

Property	Haar	Daubechie	Coiflet
Orthogonal	Yes	Yes	No
Symmetric	Yes	No	Yes
Continuous	No	Yes	Yes

Haar and Daubechies wavelets have orthogonality, which has some nice features.

1. The scaling and wavelet functions are the same for both forward and inverse transform.

2. The correlations in the signal between different subspaces are removed.

In terms of wavelet implementations, the Haar wavelet transform is the most straightforward and straightforward to implement of the bunch. This filter type suffers from a significant disadvantage due to the Haar wavelet's inability to simulate a continuous signal.

He was the one who discovered the first continuous orthogonal compact support wavelet, which he named after Daubechies. Keep in mind that the symmetry of the wavelet family has been broken in this case. In this case, symmetry is advantageous because it allows for implementing the corresponding wavelet transform using mirror boundary conditions, which reduces the number of boundary artifacts produced. It was as a result of this that the biorthogonal wavelet was created.

Table 3. Comparison of Proposed Wavelet transform with its File Size

	PSNR	CR	Mean Square Error	Compressed File Size
Haar Wavelet Compression	29.7087	3.72854	27.6829	18048 Bytes
Bi-Orthogonal Wavelet Compression	34.3987	2.64354	28.1539	16938 bytes
DCT Compression	36.3716	26.9807	14.9942	16709 bytes

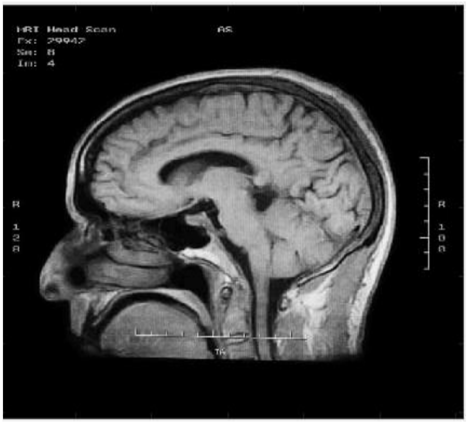

Fig.2a. Original Image

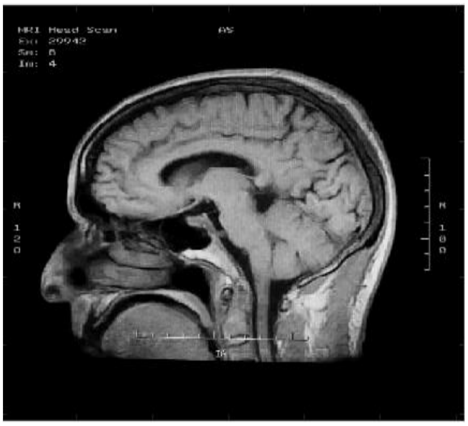

Fig.2b. Biorthogonal Wavelet Transform

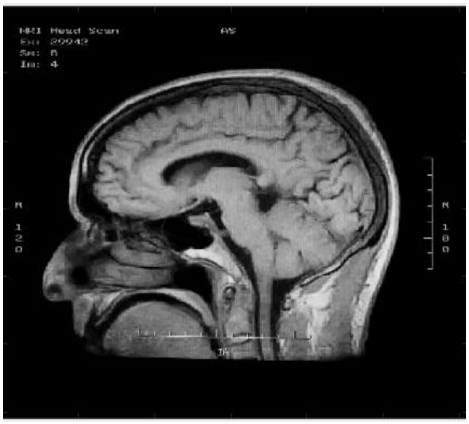

Fig.2c. Haar Wavelet Transform

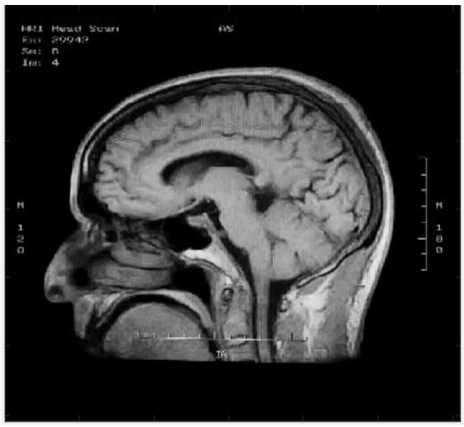

Fig.2d. DCT Compressed Image

From the data provided in the tables it is literally clear that DCT image compression has the highest CR than the other two image compression techniques and a higher PSNR making it a better compression technique to have a lowest possible size of an image. The lowest MSE I's also the DCT. Below is a graph that compares the parameters between the three image compression types. DCT compression PSNR is 7.34% higher than that of a Haar Wavelet Transform and Biorthogonal Wavelet Transform PSNR 5.73% higher than that of a Haar Wavelet Transform. Haar Wavelet Transform takes a very small amount of time to compress an image while the decompression takes a very small time in Biorthogonal Wavelet Transform.

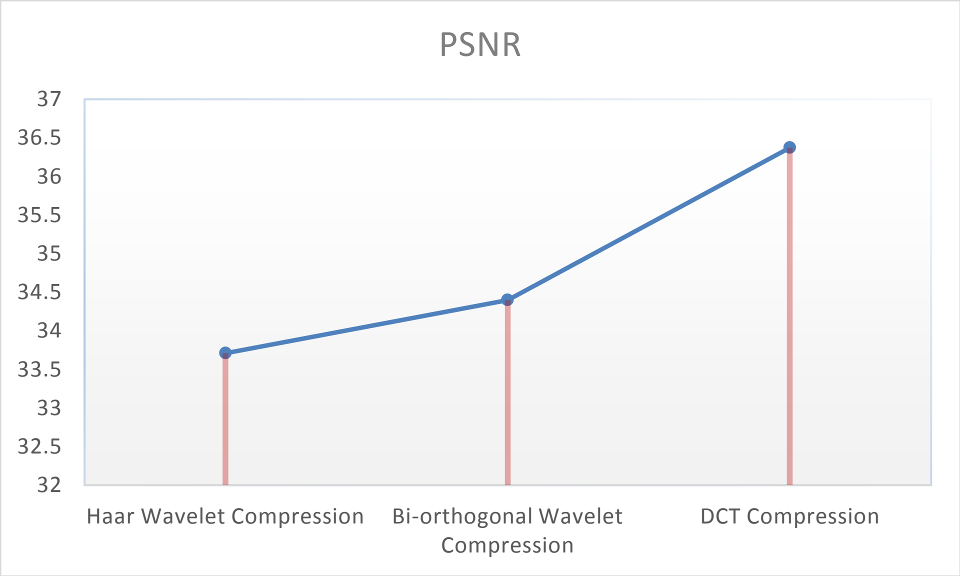

Fig.3. Comparison Graph

6. Conclusion

Compression performance of the proposed system compared between different compression techniques such as DCT, Haar wavelet transform and bi-orthogonal wavelet transform. The compression was measured in terms of compression ratio (CR), peak signal to noise ratio (PSNR), Hast wavelet transform giving a better reconstruction and higher PSNR as compared to the existing systems such as JPEG2000, EBCOT. In terms of computation time such as Encoding time (ECT) and decoding time (DCT) the Bi-orthogonal wavelet transform with combined coding and Haar wavelet transform takes less time during encoding and decoding. The results show that DCT gives a higher compression ratio when compared with other existing techniques.

6.1. Future Enhancements

The comparison of different Image compression techniques which are very vital for the a choice of the best compression technique that best fits a given purpose but it does not address certain needs that were as instrumental as those that were solved.

(1) Requirement of an automatic difference on the parameter results so that a user does not manually calculate the differences.

(2) Requirement for a graph generator of the differences so that a user visualizes the data provided in the result table so that it helps in showing how much the differences are including the improvement of documentation.

(3) Extending the user interface (UI) for the user's capability of having a good user experience such as the system's provision of information that can be useful for a user to know to what extent this system can be applied on a sample of data.

(4) Availability of a manual of how to use a he system which can be very useful for a person who does not have any knowledge and familiarity with that system.

Declarations

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Competing Interests Statement

The authors declare no competing financial, professional and personal interests.

Consent for publication

Authors declare that they consented for the publication of this research work.

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