

Compression of Medical Images using Hybrid Wavelet Decomposition Technique

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Abstract: Medical science develops very fast and therefore each hospital needs to store high volume of data about the patients. Medical images are important data about patients. So hospitals have a images with them and require a huge hard disk space and transmission bandwidth to store these images. Image compression is essential for huge database storage in various hospitals and data transfer for diagnosis. Various image compression techniques are used till now. But to improve image quality, here is the demand for new compression technique. In this paper, we provide a new compression technique with Hybrid wavelet (combination of MFHWT and Symlet wavelet) by applying Singular value decomposition method. Results are shown by comparing proposed method with the previous technique in terms of compression ratio, peak signal to noise ratio, mean square error etc. This work performs best by reducing MSE, size of compressed image and by increasing compression ratio and PSNR value.

Keywords: Haar, MFHWT, SVD, Symlet, Wavelets.

1. Introduction

Analysis and compression of medical images is an important area of biomedical engineering. Medical image examination and data compression are rapidly evolving field with growing applications in the healthcare services e. g teleradiology, e-health, tele consultation, telemedicine and statistical medical data analysis [1]. For telemedicine, medical image compression and analysis may even be more useful and can play an important role for the diagnosis of more sophisticated and complicated images through consultation of experts [2]. Data compression is the process of converting data files into smaller ones for efficiency of storage and transmission. Each compression algorithm has its corresponding decompression algorithm that, given the compressed file, should reproduce the original one. In medical image compression diagnosis and analysis are effective only when compression techniques preserve all the relevant and important image information needed. This is case of lossless compression. On the other hand lossy compression is more efficient in terms of storage and transmission needs but there is no guarantee to preserve the characteristics needed in medical diagnosis [3]. Since most digital images are intended for human observers, much research is nowadays focused on lossy compression that minimizes visual distortion and possibly obtains visually lossless results. Most of the previous wavelets decomposition reduces the information energy from the sub band frequency and does not provide finer sub bands. Thus there is a requirement of some hybrid technology that will preserve energy while compression and provides better performance in terms of performance parameters.

2. Basic Steps for Compression of an Image

Two types of compressions are possible: lossy and lossless. Wavelets, fractal compression etc. are examples of lossy compression and entropy encoding, arithmetic encoding are examples of lossless compression. There are three essential stages in a Wavelet transform image compression system: transformation, quantization and coding.

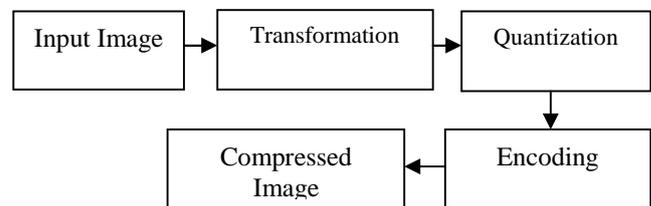


Figure 1: Basic Steps of compression

2.1 Transformation

For image compression, it is desirable that selection of transform should reduce the size of resultant data set as compared to source data set. Few transformations reduce the number of data items in the data set. Few transformations reduce the numerical size of the data items that allows them to represent by the fewer binary bits. In data compression, transform is intended to decor relate the input signals by transformation. The data represented in the new system has properties that facilitate the compression.

2.2 Quantization

In the process of quantization each sample is scaled by the quantization factor. Whereas in process of thresholding, samples are eliminated if the value of sample is less than the defined threshold value. These two methods are responsible for introduction of error and it leads in degrading the quality. The degradation is based on selection of quantization factor and threshold value. For the high value of threshold the loss of information is more, and for low value of threshold the loss of information is less. By considering the resultant loss of information, the selection of threshold should below, but for the low value of the threshold there is negligible compression of data. Hence quantization factor, or threshold value should be selected in such a way that it should satisfy the constraints of human visual system for high compression ratio and better visual quality.

2.3 Encoding

This phase of compression reduces the overall number of bits needed to represent the data set. Entropy encoder further compresses the quantized values to give better overall compression. This process removes redundancy in the form of repetitive bit patterns in the output of quantizer. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller [4].

3. Problem in Compression of an image

Image compression is a fast paced and dynamically changing field with many different types of compression methods. Images contain large amount of data hidden in them, which is highly correlated. Image compression plays a vital role in several important and diverse applications, like medical imaging, remote sensing etc. These require fast transmission and large space to store data. These requirements are not fulfilled with old techniques of compression like Fourier Transform, curvlet and Cosine Transform etc. due to large MSE occurring between original and reconstructed images. Wavelet transform or wavelet analysis is a recently developed mathematical tool for signal analysis. It is very efficient approach. Modified haar transform is also best for compression. Most of the previous wavelets decomposition reduces the information energy from the sub band frequency and does not provide finer sub bands. Thus there is a requirement of some hybrid technology that will preserve energy while compression and provides better performance in terms of compression ratio, PSNR, size of compressed file and MSE.

4. Wavelet Transforms

The wavelet transform is defined as a mathematical technique in which a particular signal is analyzed (or synthesized) in the time domain by using different versions of a dilated (or contracted) and translated (or shifted) basis function called the wavelet prototype or the mother wavelet. A wavelet function $\psi(t)$ is a small wave, which is oscillatory in some way to discriminate between different frequencies. The wavelet contains both the analyzing shape and the window. Wavelet theory has been one of the most useful developments in the last decade that developed independently on several fronts. The reason of the most wavelet research is to build more efficient wavelet function which gives precise description of the signal. But on the basis of several characteristics of the wavelets, the most suitable one can be determined for a given application. A wavelet is a small wave with finite energy, which has its energy concentrated in time or space. Comparison of a wave with a wavelet is shown in Figure 2 Left graph is a Sine Wave with infinite energy and the right graph is a Wavelet with finite energy.

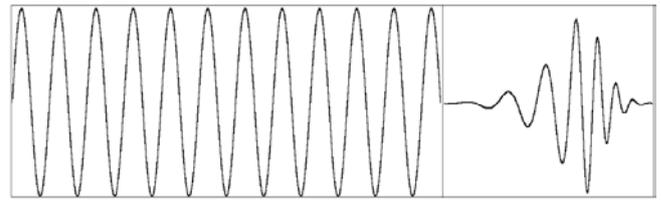


Figure 2: Comparison of a wave and wavelet

Wavelet transformation (WT) was developed to overcome the shortcoming of the Short Time Fourier Transform (STFT). While STFT gives a constant resolution at all frequencies, WT uses multi-resolution technique for non-stationary signals by which different frequencies can be analyzed with different resolutions. Wavelet theory is based on analyzing signals to their components by using a set of basis functions. One significant characteristic of the wavelet basis functions is that they are related to each other by simple scaling and translation. Original wavelet function is used to generate all basis functions. It is generally designed with respect to desired characteristics of the associated function. For multiresolution transformation, there is also a need for another function which is known as scaling function. It makes analysis of the function to finite number of components. WT is a two-parameter expansion of a signal in terms of a particular wavelet basis functions or wavelets.

4.1 2D Wavelet Transform

The principle of image compression using the DWT is analogous to that for signals. For image, DWT extended to two dimensions, Compression of an image is done using 2-D wavelet analysis. Let 'X' be an original image. It is represented by $M \times N$ matrix, where M is the number of rows and N is the number of columns in the matrix



Figure 3: (a) Original Barb image and (b) One level DWT transform

HL1, LH1 and HH1 are the highest resolution horizontal, vertical and diagonal details. The LL sub-band (low-low) is in the upper left hand corner and come from low pass filtering in both directions. It is the low resolution residual consisting of low frequency components and will be split at higher level of decomposition. Of the four components, it is the more like the original picture and so called approximation. The remaining three components are called detail components. The upper right corner comes from the high pass filtering in the horizontal direction (low) and low pass filtering in the vertical direction (columns) and so labeled HL. The visible detail in this sub-image, such as, edge, have an overall vertical orientation since there alignment is perpendicular to the direction of the high

pass filtering. Therefore they are called vertical details.

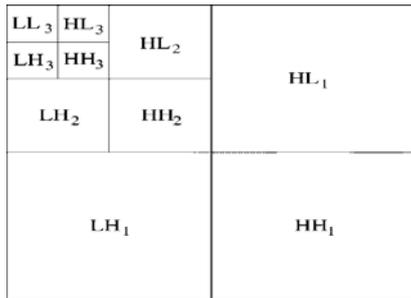


Figure 4: Approximation (LL3) and detail coefficients for the 2-D DWT.

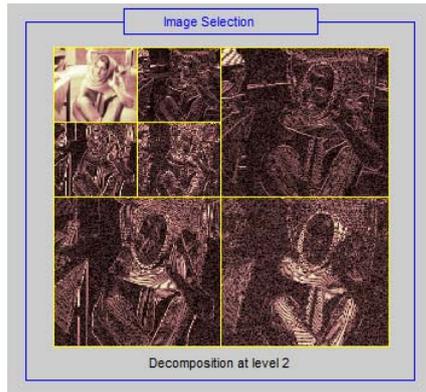


Figure 5: Two level DWT decomposition using 'haar'

5. Haar Transform

The Haar transforms (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation. A precise formula for the values of first average sub signal $\alpha^1 = (\alpha_1, \alpha_2, \dots, \alpha_{N/2})$ is defined as

$$\alpha_m = \frac{X_{2m-1} + X_{2m}}{\sqrt{2}}$$

for $m = 1, 2, 3, \dots, N/2$, where X is the input signal. The multiplication of $\sqrt{2}$ ensures that the Haar transform preserves the energy of the signal. The values of α^1 represent the average of successive pairs of X value and the first detail sub signal $d^1 = (d_1, d_2, \dots, d_{N/2})$ at the same level is given as

$$d_m = \frac{X_{2m-1} - X_{2m}}{\sqrt{2}}$$

for $m = 1, 2, 3, \dots, N/2$. The values of d^1 represents the difference of successive pairs of X value.

The first level Haar transform is denoted as H_1 . The inverse of this transformation can be achieved by

$$X = \frac{\alpha_1 + d_1}{\sqrt{2}}, \frac{\alpha_1 - d_1}{\sqrt{2}}, \dots, \frac{\alpha_{N/2} + d_{N/2}}{\sqrt{2}}, \frac{\alpha_{N/2} - d_{N/2}}{\sqrt{2}}$$

The successive level of the transform, the approximation and detail component is calculated in the same way, except that

these two components are calculated from the previous approximation component only.

6. Fast Haar Transform

It consists of addition, subtraction and division by 2, due to which this becomes faster and reduces the calculation work in comparison to haar transform. For the decomposition of an image, we first apply 1D FHT to each row of pixel values of an input image matrix. Then these transformed rows are themselves an image and we apply the 1D FHT to each column. The resultant values are all detail coefficients.

7. Modified Fast Haar Wavelet Transform (MFHWT)

In MFHWT, first average sub signal ($a' = a_1, a_2, a_3 \dots a_{N/2}$), at one level for a signal of length N i.e. $f = (f_1, f_2, f_3, f_4 \dots f_n)$ is

$$a_m = \frac{f_{4m-3} + f_{4m-2} + f_{4m-1} + f_{4m}}{4}, m = 1, 2, 3, \dots, N/4,$$

and first detail sub-signal ($d' = d_1, d_2, d_3 \dots d_n$), is given as (at the same level):

$$d_m = \begin{cases} \frac{(f_{4m-3} + f_{4m-2}) - (f_{4m-1} + f_{4m})}{4}, & m = 1, 2, 3, \dots, N/4, \\ 0 & , m = N/2, \dots, N. \end{cases}$$

In this four nodes are considered two nodes as in HT and FHT. The MFHWT is faster in comparison to FHT and reduces the calculation work. In MFHWT, we get the values of approximation and detail coefficients one level ahead than the FHT and HT [5, 6].

8. Symlet Wavelet

In sym N , N is the order. Some authors use $2N$ instead of N . The symlets are nearly orthogonal, symmetrical and biorthogonal wavelets proposed by Daubechies as modifications to the db family. Properties of the two wavelet families are similar.

Advantages

- 1) Symlets are "symmetrical wavelets".
- 2) They are designed so that they have the least asymmetry and maximum number of vanishing moments for a given compact support.

Disadvantages

- 1) These are not perfectly symmetrical.

9. Singular Value Decomposition

Singular Value Decomposition (SVD) is said to be a significant topic in linear algebra by many mathematicians. It has many practical and theoretical values; special feature of SVD is that it can be performed on any real (m, n) matrix. Let's say we have a matrix A with m rows and n columns, with rank r and $r_j \leq n \leq m$ Then the A can be factorized into three matrices:

$$A = USV^T$$

Where Matrix U is an $m \times m$ orthogonal matrix,

$$U=[u_1, u_2, \dots, u_r, u_{r+1}, \dots, u_m]$$

column vectors u_i for $i = 1, 2, \dots, m$, form an orthonormal set:

$$u_i^T u_j = \delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$

$$\begin{matrix} \boxed{A} & = & \boxed{U} & \boxed{S} & \boxed{V^T} \\ m * n & & m * m & m * n & n * n \end{matrix}$$

And matrix V is an $n \times n$ orthogonal matrix

$$V=[v_1, v_2, \dots, v_r, v_{r+1}, \dots, v_n],$$

column vectors v_i for $i = 1, 2, \dots, n$, form an orthonormal set:

$$v_i^T v_j = \delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$

Here, S is an $m \times n$ diagonal matrix with singular values (SV) on the diagonal. The matrix S can be showed in following

$$S = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_r & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & \sigma_{r+1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & \sigma_n \\ 0 & 0 & \dots & 0 & 0 & \dots & 0 \end{bmatrix}$$

For $i = 1, 2, \dots, n$, σ_i are called Singular Values (SV) of matrix A. It is proved that

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0, \text{ and} \\ \sigma_{r+1} = \sigma_{r+2} = \dots = \sigma_N = 0.$$

For $i = 1, 2, \dots, n$ σ_i are called Singular Values (SVs) of matrix A. The v_i 's and u_i 's are called right and left singular vectors of A.

9.1 SVD approach for Image Compression

Image compression deals with the problem of reducing the amount of data required to represent a digital image. Compression is accomplished by the removal of the basic data redundancies:

- 1) Coding redundancy, which is present when less than optimal;
- 2) Interpixel redundancy, results from correlations between the pixels;
- 3) Psycho visual redundancies, is due to data that is ignored by the human visual [7].

The rank of matrix A is equal to the number of its non-zero singular values. In most applications the singular values of a matrix decrease quickly with increasing rank. This property allows us to reduce the noise or compress the matrix data by eliminating the small singular values or the higher ranks.

When an image is SVD transformed, the image is not compressed, but the data take a form in which the first singular value has a great amount of the image information. By this, we can use only a few singular values to represent the image with little differences from the original.

$$A = USV^T = \sum_{i=1}^r \sigma_i u_i v_i^T$$

i.e A can be represented by the outer product expansion:

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T$$

When compressing the image, the sum is not performed to the very last SVs, the SVs with small enough values are dropped. (Remember that the SVs are ordered on the diagonal). Closet matrix of rank k is obtained by truncating those sums after the first k terms:

$$A_k = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_k u_k v_k^T$$

The total storage for A_k will be $k(m+n+1)$

The integer k can be chosen confidently less than n, and digital image corresponding to A_k still have very close the original image. However, when choose the different k will have a different corresponding image and storage for it. For typical choices of k, the storage required for A_k will be less than 20 percent [8].

10. Methodology Used

The method used here is to apply Hybrid wavelet (MFHWT and Symlet wavelet) on image matrices and then apply SVD on coefficients of matrices. It preserves energy while compression and provides good compression ratio. The image quality is analyzed by using many performance parameters.

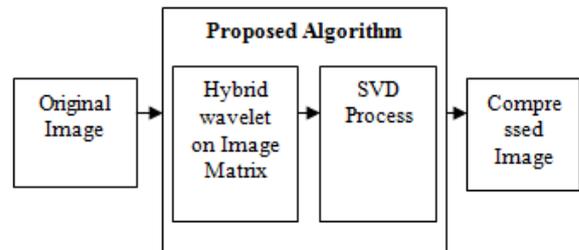


Figure 6: Methodology Used

Flowchart presenting the proposed algorithm

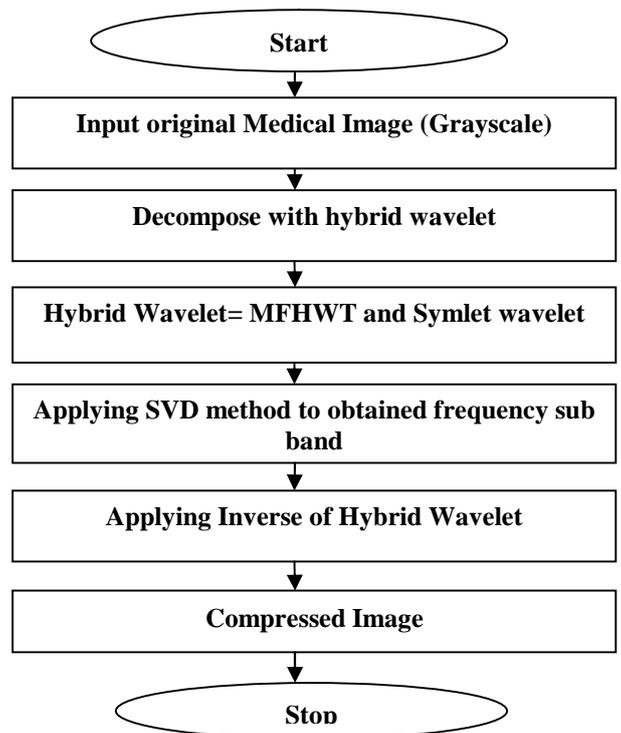


Figure 7: Diagrammatic depiction of proposed algorithm

11. Proposed Algorithm

Step 1: Read the grayscale medical image as a matrix.

Step 2: Apply Hybrid wavelet, along row and column wise on entire matrix of the image.

Step 3: Compute the approximation coefficients matrix and details coefficients matrices obtained by a Hybrid wavelet decomposition of the input matrix.

Step 4: Apply Singular value decomposition (SVD) on approximation coefficients matrix

So that it produce a diagonal matrix, of the same dimension as image matrix and with nonnegative diagonal elements in decreasing order, and also unitary matrices.

Let's say we have a matrix A with m rows and n columns, with rank r and $r_1 \leq n \leq m$ Then the A can be factorized into three matrices:

$$A=USV^T$$

Where Matrix U is an $m \times m$ orthogonal matrix, V is an $n \times n$ orthogonal matrix and S is an $m \times n$ diagonal matrix with singular values (SV) on the diagonal.

Step 5: For reconstructing the image, applying the inverse.

Step 6: Calculate PSNR, MSE, Compression ratio and size for reconstructed image.

12. Performance Parameters

For comparing original image and uncompressed image, we calculate following parameters:

(i) Mean Square Error (MSE): The MSE is the cumulative square error between the encoded and the original image defined by:

$$MSE = \frac{1}{mn} \sum_0^{m-1} \sum_0^{n-1} \|f(i, j) - g(i, j)\|^2$$

Where, f is the original image and g is the compressed image. The dimension of the images is $m \times n$. Thus MSE should be as low as possible for effective compression. MSE measures average of the square of the "error." The error is the amount by which the estimator differs from the quantity to be estimated.

(ii) Peak signal to noise ratio(PSNR): the ratio between the maximum possible power of a signal and the power of distorting noise which affects the quality of its representation defined by:

$$PSNR = 20 \log_{10} \left(\frac{MAX_f}{\sqrt{MSE}} \right)$$

where MAX_f is the maximum signal value that exists in our original image. A matching image to the original will give in an undefined PSNR as the MSE due to no error, will become equal to zero. In this case the PSNR value can be thought of as approaching infinity as the MSE approaches zero; this shows that a higher PSNR value provides a higher image quality.

iii) Compression ratio (CR): The compression ratio is defined as the size of the original image divided by the size of the compressed image. The ratio provides a clue of how much compression is achieved for a particular image.

iv) Size of compressed file: Image compression is to minimize the size of a graphics file without degrading the

quality of the image. The reduction in size allows more images to be stored in a given amount of disk or memory space. It reduces the time required for images to be sent over the Internet.

13. Results and Discussions

This section presents the results of combined effect of Hybrid wavelet with SVD on to the medical images in MATLAB to observe the change in PSNR, MSE, Compression ratio and size of the image. The performance of the method is illustrated with both quantitative and qualitative performance measure. The qualitative measure is the visual quality of the resulting image. PSNR, MSE, compression ratio and compressed image size are used as quantitative measure. This section provide the result of image compression techniques like MFHWT and proposed method and determine that proposed method is best for image compression.



(a) Original image



(b) MFHWT Method Compression



(c) Proposed Method Compression

Figure 8: Hand Images



(a) Original image



(b) MFHWT Method Compression



(c) Proposed Method Compression

Figure 9: Knee Images

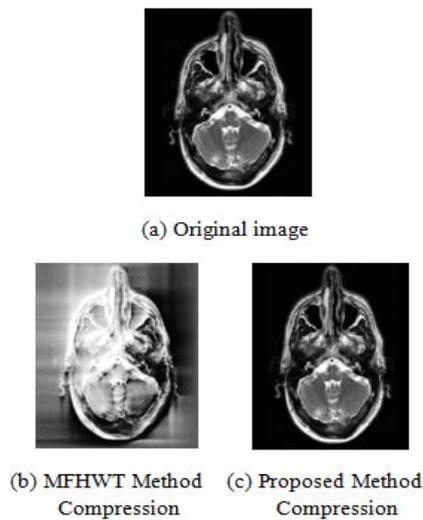


Figure 10: Brain Images

The original image, image compressed with MFHWT and image compressed with proposed method of hand, knee and brain are shown in figure 8,9,10 respectively. It is clear that the proposed method works properly in terms of visual quality.

Table 1: Values of parameters attained by MFHWT and Proposed method for image “Hand” with original size 35 kb

S. No	Parameter	MFHWT	Proposed
		Method	Method
1	PSNR(db)	16.3381	21.3639
2	MSE	8209	475
3	CR	1.9444	2.1875
4	Compressed Image Size(kb)	18	16

Table 2: Values of parameters attained by MFHWT and Proposed Method for image “Knee” with original size 28 kb

S. No	Parameter	MFHWT	Proposed
		Method	Method
1	PSNR(db)	20.8724	21.5078
2	MSE	1712	1414
3	CR	1.75	2.3333
4	Compressed Image Size(kb)	16	12

Table 3: Values of parameters attained by MFHWT and Proposed Method for image “Brain” with original size 26 kb

S. No	Parameter	MFHWT Method	Proposed Method
1	PSNR(db)	16.602	17.5264
2	MSE	7365	5164
3	CR	0.96154	1.1364
4	Compressed Image Size(kb)	26	22

Table 1, 2 and 3 shows the comparison of MFHWT and proposed method in terms of performance parameters.

14. Conclusion

The proposed method presents the results of changing the MFHWT method and applying Hybrid wavelet with SVD on to the images to observe the change in parameters value. The performance of the method is illustrated with both quantitative and qualitative performance measure. The qualitative measure is the visual quality of the resulting image. PSNR, MSE, compression ratio are used as quantitative measure. This validates the assumption that image compression using hybrid wavelet with SVD is very good model. Performance of proposed method has been analyzed and a number of practical experiments with various medical images are present. From the visual inspection one can easily determine the difference between the qualities of compressed image in both methods and hence performance of the proposed technique is evaluated. Our methods give fairly satisfying results in both visual and numerical aspects. In addition, they are considerably effective and easy to implement.

15. Future scope

In future, to get the better result new wavelets can be blended with other schemes. So, new parameters can be considered for the evaluation of compression techniques. Optimization of various compression techniques can be done to preserve energy and better results as much as possible. In Future, we can combine the contour wavelet transformation with pyramid and using MFHWT to get better quality of images and performance parameters.

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