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IMWT CODING USING LOSSY IMAGE COMPRESSION TECHNIQUES FOR SATELLITE IMAGES

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ABSTRACT

The performance of the wavelets in the field of image processing is well known. It is experimental with multiplicity of different images types are compressed using a fixed wavelet filter. In this work Integer Multiwavelet Transform (IMWT) algorithm for Lossy compression has been derived for three different types of images like Standard Lena, Satellite urban and Satellite rural. The IMWT shows high performance with reconstruction of the images. This work analyses the performance of the IMWT for lossy compression of images with Magnitude Set-Variable length Integer coding. The Transform coefficients are coded using the Magnitude set coding and run length Encoding techniques. The sign information of the coefficients is coded as bit plane with zero thresholds. The Peak Signal to Noise Ratios (PSNR) and Mean Square Error (MSE) obtained for Standard images using the Proposed IMWT lossy compression scheme. The effectiveness of the lossy compression method can be evaluated by examining the Image with 8-bit Gray (256x256) pixels. The results confirm that Standard Lena, Satellite rural and urban images are better suited for proposed scheme compared to that of Existing SPIHT (Set Partitioning in Hierarchical Trees) Lossy algorithm. The Simulation was done in Mat lab.

Keywords: IMWT, compression MSE, PSNR, and Magnitude set coding, run length coding, Bit plane coding.

1. INTRODUCTION

Data Compression is the art or science of representing information in a compact form. It is used to reduce the number of bits required to represent an image or a video sequence. A Compression algorithm takes an input X and generates compressed information that requires fewer bits. The Decompression algorithm operates on the compressed information to generate the reconstruction Y. Based on the reconstruction Y, the compression algorithms are broadly classified into two categories, namely Lossy and Lossy compression Algorithms.

1.1 Lossless compression

These techniques, involve no loss of information. The Original information can be recovered exactly from the compressed data. It is used for applications that cannot tolerate any difference between the original and the reconstructed data.

1.2 Lossy compression

It involves some loss of information. The data that have been compressed using lossy techniques generally cannot be recovered or reconstructed exactly. It results in higher compression ratios at the expense of distortion in reconstruction. Compression Techniques can be applied directly toward the images or to the transformed image information (transformed domain). The Transform coding techniques are well suited for image compression. Here the image is decomposed or transformed into components that are then coded according to the individual characteristics. The transform should posses' high-level compaction property, so as to achieve high compression ratios. The Performance of a Compression method can be evaluated in a number of ways: the relative complexity of the technique, Memory requirement for implementation, Speed of the Technique on a machine, the amount of compression, and the distortion rate in the reconstructed image.

Compression Ratio (CR): It is the ratio of the number of bits required to represent the image before compression to the number of bits required to represent the image after compression.

Data Rate: It is defined as the average number of bits required to represent a single sample. It is specified in terms of Bits per Pixel (Bpp).

Distortion: The difference between the original and reconstructed image is called as Distortion. It is denoted using Mean Square Error (MSE) in dB.

$$MSE(dB) = 10\log_{10}\left[\frac{1}{NXN}\sum_{i=0}^{NXN}(X_i - Y_i)^2\right] \tag{1}$$

Fidelity or Quality: It defines the resemblance between the Original and Reconstructed image. It can be measured using Peak Signal to Noise Ratio (PSNR) in dB.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) dB \tag{2}$$

1.3 Overview of the proposed work

In this work the image is transformed using Integer Multiwavelet transform and Lossy Compression of the transform coefficients is done with Magnitude set coding and Run Length Coding as shown in Figure-1. The Algorithms were implemented in Mat lab.

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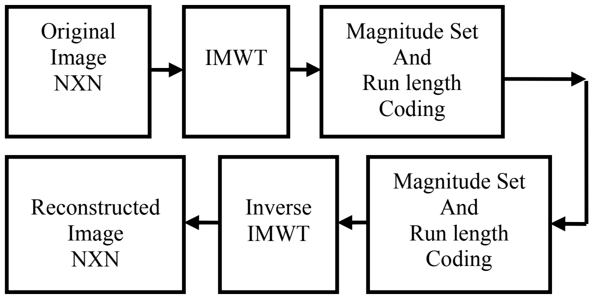

Figure-1. Block diagram.

2. WAVELET TRANSFORM

The Fourier Transform which is the transform well known to engineers has sinusoidal waves as the orthonormal basis. For this integral transform, the basic functions extend to infinity in both directions. Transient Signal components are nonzero only during a short interval. In Images, many important features like edges are highly localized in spatial position. Such components do not resemble any of the Fourier basis functions and they are not represented compactly in the transform coefficients. Thus the Fourier Transform and other wave transforms are less optimal representations for compressing and analyzing signals and images containing transient or localized components. Wavelets are a result of the time frequency analysis of the signals in terms of a two-dimensional time-frequency space.

2.1 Fundamentals of wavelet transform

In wavelet analysis, we generate a set of basic functions by dilating and translating a single prototype function, $\Psi(x)$, which is the basic wavelet. This is some oscillatory function usually centered upon the origin, and dies out rapidly as $|x| \rightarrow \infty$. A set of wavelet basis functions, $\{\Psi_{a,b}(x)\}$,[5] can be generated by translating and scaling the basic wavelet as,

$$\Psi_{a,b}(x) = (1/\sqrt{a}) * \Psi((x-b)/a) \quad (3)$$

Where a>0 and b are real numbers. The variable 'a' reflects the scale (width of the basis wavelet) and the variable 'b'specifies its translated position along the x-axis and $\Psi(x)$ is also called as mother wavelet.

2.2 2-D Discrete wavelet transform

The concepts developed for the representation of one-dimensional signals generalize easily to two-dimensional signals. For the 2-D Discrete Wavelet transform implementation is based on the pyramidal algorithm developed for multi resolution analysis of the signals. The Pyramidal Algorithm is based upon the Filter bank theory. The wavelet function and the scaling function are chosen. These functions are then used to form the dilation equation. The wavelet dilation equation represents the high pass filter. The scaling dilation equation represents the low pass filter. These filter coefficients are then used to construct the filters. Let h (n) is the low pass filter and g (n) is the high pass filter. Then for the perfect reconstruction, it has to satisfy some properties [5] in frequency domain, such as,

$$|H(w)|^2 + |H(w+\Pi)|^2 = 1 \quad (4)$$

$$|H(w)|^2 + |G(w)|^2 = 1 \quad (5)$$

The Filter structure of the Pyramidal Algorithm for I-(first) level Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) is shown in Figure-2 and Figure-3.

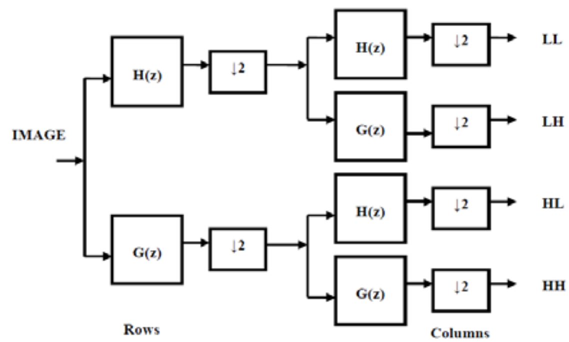

Figure-2. I- Level DWT filter implementation.

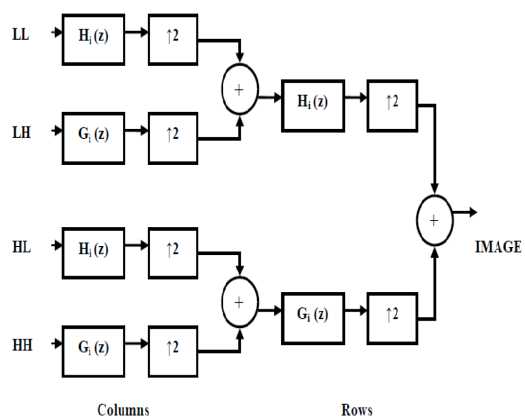

Figure-3. IDWT Filter Implementation.

Where H (z) is the Low pass Analysis Filter and G (z) is High Pass Analysis Filter, H_i (z) is the Low pass Synthesis Filter and G_i (z) is high pass Synthesis Filter. The Wavelets are particularly attractive, as they are capable of capturing most image information in the highly sub sampled low frequency band (LL) also called as the approximation signal. The additional localized edge information in spatial clusters of coefficients will be in the high frequency bands (HL, LH, and HH). Another attractive aspect of the course to fine nature of the wavelet representation naturally facilitates a transmission feature that enables progressive transmission as an embedded bit stream.

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3. MULTIWAVELET TRANSFORM

Multiwavelet transform are very similar to the wavelet transform, but have some specific differences. Wavelet transform makes use of a single scaling function and wavelet function, hence also called as scalar wavelet transform. Multiwavelet transform has more than one scaling function and wavelet function. The scaling functions and wavelet functions are grouped into vectors. The number of such functions that are grouped forms the multiplicity of the transform. For notational convenience, Multiwavelet transform with multiplicity 'r' can be written using a vector notation $\phi(t) = [\phi_1(t), \phi_2(t)\dots \phi_r(t)]$, the set of scaling functions and $\psi(t) = [\psi_1(t), \psi_2(t), \dots, \psi_r(t)]$, the set of wavelet functions [1]. When r =1 then it forms the scalar wavelet transform. If r>=2 it becomes Multiwavelet Transform. Up to date Multiwavelet transforms of multiplicity r = 2 are studied. As with the scalar wavelet transform the multiwavelet transform also has a set of dilation equation that gives the filter coefficients for the low pass and high pass filters [12]. Multiwavelet transform with multiplicity two has two low pass filters and two high pass filters [13], [18]. Examples include GHM, CL, and IMWT. The Multiwavelet two dilation equations resemble those of scalar wavelets and are given as [4], [8].

$$\varphi(t) = \sum_k H_k \quad \varphi(2t - k) \tag{6}$$

$$\psi(t) = \sum_k G_k \quad \psi(2t - k) \tag{7}$$

Where H_k, G_k are the low pass and high pass multifilter coefficients respectively. With Multiwavelets there are more degrees of freedom to design the system. For instance, simultaneous possession of orthogonality, short support, symmetry and high approximation order is possible in multiwavelet system. That comprise been deliberate extensively (see, e.g., [2] and [10]).

3.1 Multiwavelet decomposition

The decomposition of a (NXN) image by Multiwavelet transform is depicted in the Figure-4. First the image is prefiltered along the row direction, and then processed by the multiwavelet filters in the same direction. Then the same processing is done in the column direction for the resultant image. The final result produces the sixteen subbands.

3.2 Integer multiwavelet transform

The Integer Multiwavelet transform is based on the box and slope scaling functions. The system is based on the multi scaling and multiwavelts given by,

$$\begin{bmatrix}\varphi(t)\\ \varphi_2(t)\end{bmatrix} = \begin{bmatrix}1 & 0\\ -1/2 & 1/2\end{bmatrix}\begin{bmatrix}\varphi(2t)\\ \varphi_2(2t)\end{bmatrix} + \begin{bmatrix}1 & 0\\ 1/2 & 1/2\end{bmatrix}\begin{bmatrix}\varphi(2t\\ \varphi_2(2t\end{bmatrix} \tag{8}$$

$$\begin{bmatrix}\psi(t)\\ \psi_2(t)\end{bmatrix} = \begin{bmatrix}1/2 & 1/2\\ 0 & 0\end{bmatrix}\begin{bmatrix}\psi(2t)\\ \psi_2(2t)\end{bmatrix} + \begin{bmatrix}1/2 & 1/2\\ 0 & 0\end{bmatrix}\begin{bmatrix}\psi(2t)\\ \psi_2(2t)\end{bmatrix} \tag{9}$$

The Integer Multiwavelet Transform (IMWT) has short support, symmetry, high approximation order of two. It is a block transform. It can be efficiently implemented with bit shift and addition operations [3], [7]. Another advantage of this transform is that, while it increases the approximation order, the dynamic range of the coefficients will not be largely amplified, an important property for Lossy coding.

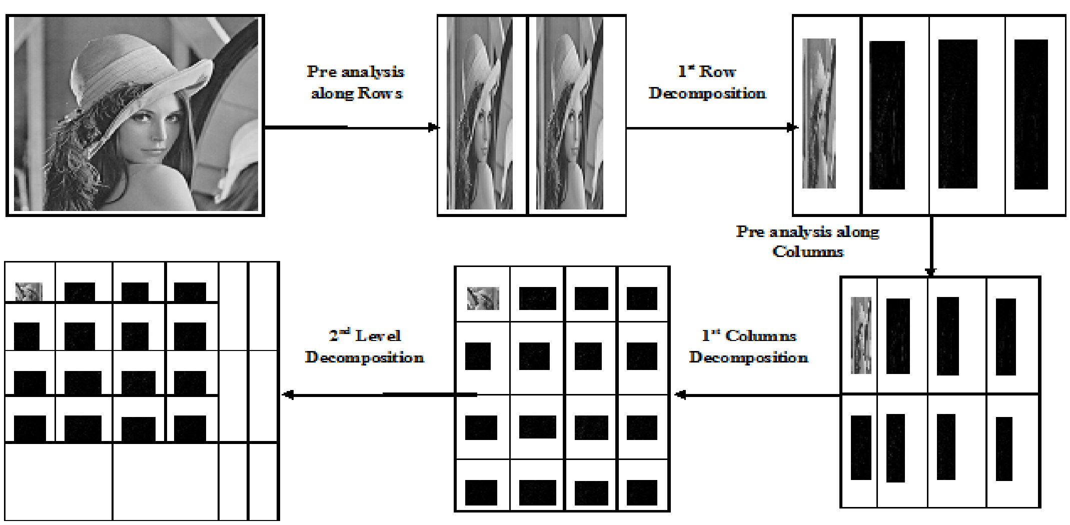

Figure-4. 2-D Multiwavelet decomposition of an image.

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4. LOSSY CODING OF TRANSFORM COEFFICIENTS

The Integer Multiwavelet Transform produces coefficients of both positive and negative magnitudes. These coefficients have to be coded efficiently so as to achieve better compression ratios. The coefficients of the H_1H_1, H_1H_2, H_2H_1, and H_2H_2 have only the edge information and are mostly zeros. This helps in having some redundancy in the subband, which can be exploited for compression. In this work two lossy coding schemes are grouped together to obtain better compression. Each Transform coefficient has sign and magnitude part in it. Magnitude Set coding is used for the compression of the magnitude and Run Length Encoding is used for coding the sign part of the coefficients. Two methods based on the Magnitude Set coding and run length encoding has been tested for the Lossy Compression of the Integer Multiwavelet Transform coefficients [16], [17].

4.1 Magnitude set–variable length integer representation

The proposed Magnitude Set - Variable Length Integer Representation (MS-VLI) is the Transformed coefficients that are grouped into different Magnitude Sets in both the methods. Each coefficient has three parameters namely (Set, Sign, and Magnitude) in MS-VLI [6], [9] and [11] coding. The Set information is arithmetically coded, followed by a bit for Sign then followed by Magnitude information in bits. In MS-VLI the sign bit is eliminated from the parameter list. It separately coded using RLE method. Each coefficient is coded with two parameters (Set, Magnitude).The magnitudes of the coefficients are grouped into different Magnitude sets according to the Table-1.

Table-1. Definition of magnitude set variable length integer representation.

Magnitude set	Amplitude intervals	Magnitude bits
0	[0]	0
1	[1]	0
2	[2]	0
3	[3]	0
4	[4 -5]	1
5	[6 - 7]	1
6	[8 – 11]	2
7	[12 – 15]	2
…..	…….	…..

The coefficients with zero magnitude have no sign information for coding. The Magnitude Set itself is used. The decoding is simple. The magnitudes of the coefficients are reproduced with the Set and Magnitude information. Then the sign bits are applied to each. If a coefficient is zero in magnitude, no sign bit has to be applied, search for the next non-zero coefficient. Searching the non-zero coefficients according to the scan order and applying the Run Length Decoded sign information remains the decoding algorithm. From the analyses of the Integer Multiwavelet Transform, it has been found that the L_1L_1 subband has always-positive coefficients. Thus the sign information of that subband is not coded. Thus for a NXN image the sign information of an N/4 X N/4 is not required. It is implied that the first subband values are positive.

5. COMPRESSION ALGORITHM STEPS AND DISCURSIONS

5.1 Algorithm steps

Step-1: Apply original (N x N) gray Image as Input using pre-filter and Forward Integer Multiwavelet Transform for Pre-analysis along rows.

Pre-filter row:

$$P^{(0)}{}_{r1,i} = \left[(P_{2i} + P_{2i+1})/2\right] \quad (10)$$

$$P^{(0)}{}_{r2,i} = P_{2i+1} - P_{2i}, \quad (11)$$

Step-2: Apply Integer Multiwavelet Transform by Pre-analysis along columns.

Pre-filter column:

$$P^{(0)}{}_{c1,i} = \left[(P_{2i} + P_{2i+1})/2\right] \quad (12)$$

$$P^{(0)}{}_{c2,i} = P_{2i+1} - P_{2i}, \quad (13)$$

Step-3: Apply Magnitude Set and Run length coding for decomposition across transformed values.

Step-4: Store the Encoded values and find the compression ratio.

Step-5: Decode the encoded values and get the transformed image.

Step-6: Apply the Inverse Integer Multiwavelet Transform for image reconstruction.

Step-7: The final output is resultant of compressed reconstructed (N x N) gray image.

The above Algorithm steps implemented to find the best compression with reconstruction among the LossyMethod-1 and Method-2. As a result comparison of proposed two Lossy compression methods scheme (MS-VLI Including RLE) and (MS-VLI Excluding RLE) for 8-bit Lena (256 * 256) image is given below,

5.1.1 Method-1

Compression Steps for MS-VLI excluding Run length Encoding Algorithm:

Step-1: Obtain the Total number of Pixels for the Original Input (N x N) gray Image.

Step-2: Identify the Total number of bits required before Compression by (N x N) x 8-bits.

Step-3: Identify Number of Sign bits.

Step-4: Calculate the Number of bits in Sign Plane encoded in RLE.

Step-5: Identify the .Number of bits for magnitude using (N x N) x 5-bits per pixel.

Step-6: To Calculate Total bits Sum the equivalents of (Number of Sign Bits obtained + Number of bits in Sign Plane encoded in RLE obtained + Number of bits for magnitude obtained).

Step-7: Calculate the Compression Ratio by Total number of bits summed divided by (N x N).

5.1.2 Method-2

Compression Steps for MS-VLI including Run length Encoding Algorithm:

Step-1: Obtain the Total number of Pixels for the Original Input (N x N) grey Image.

Step-2: Identify the Total number of bits required before Compression by (N x N) x 8-bits.

Step-3: Identify Number of Sign bits.

Step-4: Calculate the Number of bits in Sign Plane encoded in RLE.

Step-5: Identify the Number of bits for magnitude using RLE.

Step-6: To Calculate Total bits Sum the equivalents of (Number of Sign Bits obtained + Number of bits in Sign Plane encoded in RLE obtained + Number of bits for magnitude obtained).

Step-7: Calculate the Compression Ratio by Total number of bits summed divided by (N x N).

The reduction of (4 to 6) Bits per pixels from the lossy based method is due to the omission of the sign bits of L_1L_1 subband and the Run Length Encoding of the sign bits using bit planes. This small reduction can prove useful for progressive transmission of images where bandwidth is limited and satellite applications.

Table-2 shows the results of Existing SPIHT algorithm based lossy compression method of Standard Lena, Satellite urban and Satellite rural images [15]. The Proposed IMWT algorithm based lossy compression performance constantly output Existing SPIHT algorithm based lossy compression method, As expected higher desertion moment as compared with SPIHT method, Increasing the energy optimization competence of proposed IMWT method and thus resultant in better compression performance than that of Existing SPIHT method. It must be pointed out that unlike Existing SPIHT lossy method the proposed IMWT lossy method being the simplest Integer multiwavelet transformation and has not exploits the pixel correlation among the neighbor blocks, Thus Integer multiwavelet transform is promising direction for lossy coding.

Table-2. Proposed IMWT based and existing SPIHT based Lossy method with PSNR in (dB) and Compression Ratio (CR).

Image type (256x256)	**Existing SPIHT algorithm based lossy method**		**Proposed IMWT algorithm based lossy method**	
	PSNR (dB)	**CR**	**PSNR (dB)**	**CR**
Standard Lena	35.81	8	37.12	8
Satellite urban	19.00	8	20.39	8
Satellite rural	12.60	8	14.77	8

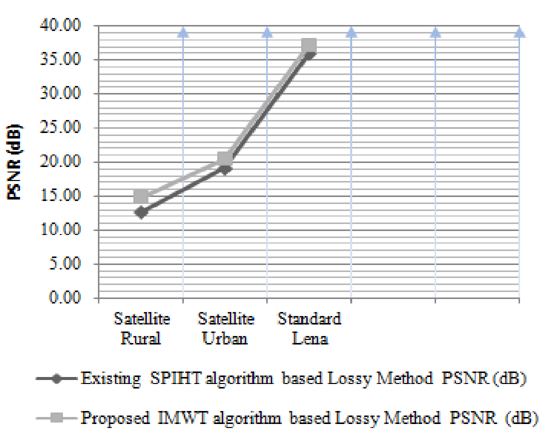

Figure-5. Existing SPIHT and Proposed IMWT Algorithm Based Lossy Methods PSNR (dB).

6. MATLAB SIMULATION RESULTS

The Integer Multiwavelet Transform was first implemented in Mat lab. The RLE algorithm was applied to various images and the MSE and PSNR values in dB were obtained. The sixteen subbands were also obtained with Mat lab. The reconstruction of the image from all the sixteen subbands corresponds to the Lossy reconstruction. The IMWT was tested for various standard images. The I-Level IMWT subband Decomposition for 256x256 images is expanded and shown in Figure-6.

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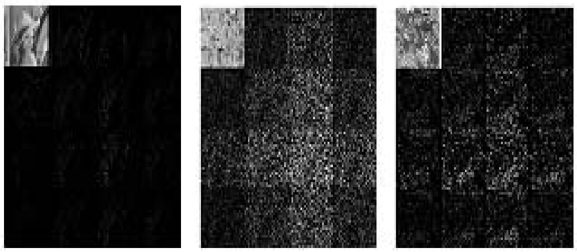


Figure-6. I-level IMWT decomposition of Standard Lena, Satellite rural and Satellite urban 256x256 image.

The First (I-level) Integer Multiwavelet Transform decomposition of the images has sixteen subbands with the L_1L_1 subband in the Top left corner. The Existing SPHIT based Lossy [14], [15] and proposed IMWT based Lossy Reconstruction for Standard Lena is shown in Figure-7. Similarly Satellite Rural and Satellite Urban showed in Figure 8 and Figure-9.

Standard Lena (256x256)Image	Existing SPIHT algorithm based Lossy Reconstructed PSNR in dB is 35.81
	
Proposed IMWT algorithm based Lossy Reconstructed PSNR in dB is 37.12 	

Figure-7. Existing SPHIT based Lossy and proposed IMWT based Lossy Reconstruction for Standard Lena 256x256 with PSNR in dB is 37.12.

On considering the Higher Quality factor, the proposed Lossy shows good quality with low-distortion compared to Existing Lossy method. The Distortion difference between the Standard Lena Image Input and Proposed Lossy Reconstructed output results as shown in Figure-10. Similarly Satellite Rural and Satellite Urban shown in Figure-11 and Figure-12.

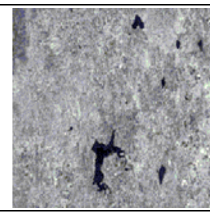
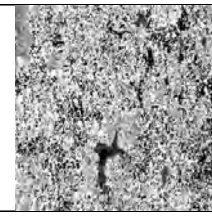
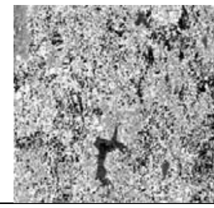
Satellite Rural (256 x 256) Image	Existing SPIHT algorithm based Lossy Reconstructed PSNR in dB is 12.60
	
Proposed IMWT algorithm based Lossy Reconstructed PSNR in dB is 14.77 	

Figure-8. Existing SPHIT based Lossy and proposed IMWT based Lossy Reconstruction for Satellite Rural 256x256 with PSNR in dB is 14.77.

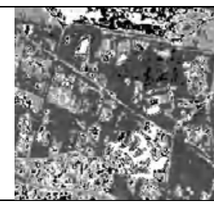
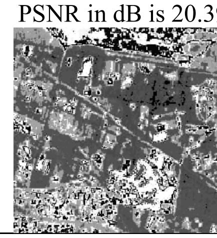
Satellite Urban (256x256) Image	Existing SPIHT algorithm based Lossy Reconstructed PSNR in dB is 19.00
	
Proposed IMWT algorithm based Lossy Reconstructed PSNR in dB is 20.39 	

Figure-9. Existing SPHIT based Lossy and proposed IMWT based Lossy Reconstruction for Satellite Urban 256x256 with PSNR in dB is 20.39.

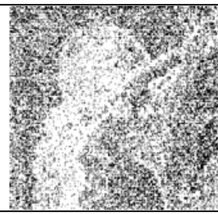
Standard Lena (256x256) Image Input	Proposed IMWT based Lossy Reconstructed
	
Reconstructed with LL-Subband alone	Lossy Distortion Output
	

Figure-10. Distortion difference between Standard Lena (256x256) Image Input and Proposed Lossy Reconstructed Output.

Table-3 shows the Maximum bit per pixels required in proposed Lossy methods after compression of Standard Lena, Satellite Urban and Satellite Rural Image. Also from the table it's identified after compression the proposed two Lossy methods shows result of maximum bits required in method-1 and method-2 and the results Identified that method-1 requires higher (Bpp) compared to method-2 which requires very low (Bpp).

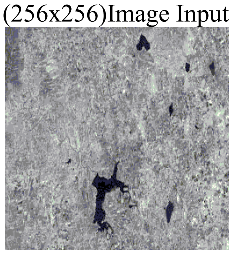
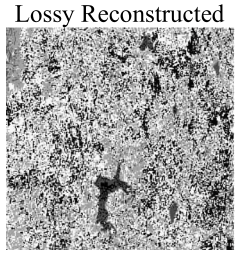
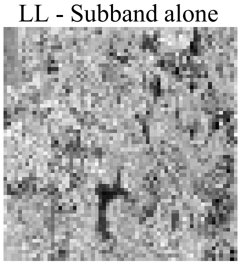
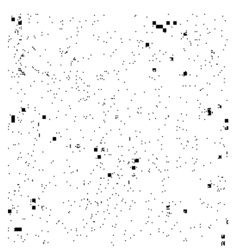
Satellite Rural (256x256)Image Input	Proposed IMWT based Lossy Reconstructed
	
Reconstructed with LL - Subband alone	Lossy Distortion Output
	

Figure-11. Distortion difference between Satellite Rural (256x256) Image Input and Proposed Lossy Reconstructed Output.

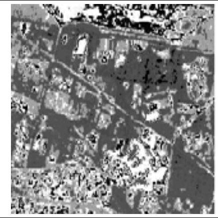
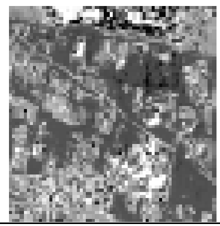
Satellite Urban (256x256) Image Input	Proposed IMWT based Lossy Reconstructed
	
Reconstructed with LL-Subband alone	Lossy Distortion Output
	

Figure-12. Distortion difference between Satellite Urban (256x256) Image Input and Proposed Lossy Reconstructed Output.

Table-4 gives the PSNR and MSE values of results in dB for reconstructed standard images using method-2. The Lena, Urban and Rural Images on Lossy Reconstruction with LL-Subband alone provide Minimum (MSE in dB) and Maximum (PSNR in dB).

Table-3. Proposed methods after compression with maximum required bits per Pixels.

Image (256x256) **Pixels**	**Proposed IMWT based lossy method after compression**	
	Method-1 Max (Bpp) **required**	**Method- 2 Max** (Bpp) **required**
Lena	6	2
Urban	7	3
Rural	8	4

Table-4. PSNR and MSE values in dB for reconstructed images.

Image (256x256) **Pixels**	**Proposed IMWT lossy reconstruction with LL - subband**	
	MSE (dB)	**PSNR (dB)**
Lena	11.0028	37.1272
Urban	27.7355	20.3945
Rural	33.3553	14.7747

The MSE and PSNR for Satellite images were identified high-quality by using method-2. The performance of IMWT for images with high frequencies was outstanding. The subjective quality of the reconstructed image by retaining the LL- subband information alone (comprising of L_1L_1, L_1L_2, L_2L_1, L_2L_2 subbands) is equal to that of Lossy reconstruction. This proves the performance of Multiwavelet that allows more design freedom.

7. ACKNOWLEDGMENT

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8. CONCLUSIONS

The performance of the Integer Multiwavelet Transform for the Lossy compression of images was analyzed. It was found that the IMWT can be used for Lossy compression techniques. The standard images used for testing by this lossy compression technique provide a high quality of results on reconstruction. The IMWT produces good results even with artificial images and images with more high frequency content like satellite images, forest scenes, etc.The bit rate obtained using the MS-VLI Including RLE scheme is about (4-bpp to 6- Bpp) less than that obtained using MS-VLI Excluding RLE scheme.

REFERENCES

[1] Gang Lin, Ze-Min Liu. 2000. "The Application of Multiwavelet Transform to Image Coding", IEEE Transaction on Image Processing, Vol.9, No.2 pp. 270-273.

[2] Jo Yew Tham, Lixin Shen, Seng Luan Lee, Hwee Huat Tan. 2000. "A General Approach for analysis and application of Discrete Multiwavelet Transforms", IEEE Transaction on Signal Processing, Vol.48, No.2 pp 457- 464. (February 2000).

[3] Kwok-Wai Cheung, Lai-Man Po. 2001. "Integer Multiwavelet Transform for Lossy Image Coding", Proceedings of 2001 International Symposium on Intelligent Multimedia, Video and Speech Processing, pp. 117 – 120.

[4] Mariantonia Cotronei, Damiana Lazzaro, Laura B. Montefusco, Luigia Puccio. 2000. "Image Compression Through Embedded Multiwavelet Transform Coding", IEEE Transactions on Image Processing, Vol. 9 NO. 2, pp. 184 – 189.

[5] Raghuveer M.Rao, Ajit S.Bopardikar.1998. "Wavelet Transforms", – Introduction to Theory and Applications.

[6] G.ATriantafyllidis, M.G. Strintzis.1999. "A context Based Adaptive Arithmetic coding Technique for Lossy Image Compression", IEEE Signal Processing Letters, Vol. 6, No.7, pp. 168 – 170.

[7] R.Calderbank, I.Daubechies, W.Sweldens, B.L.Yeo. 1997. "Lossy image compression using integer to integer wavelet transform", in Froc.IEEE Conf.on Image Fmc.1997, IEEE Press.

[8] J.Y.Tham, S.Ranganath, A.A.Kassim.1998. "Highly scalable wavelet - based video compression for very low bit-rate environment", IEEE J.Select Areas Commun-Special Issue on Very low Bit-Rate Video Coding, vol.16, pp.12-27, (January1998).

[9] N.Memon, X.Wu, B.L.Yeo.1997. "Entropy coding techniques for Lossy image compression with reversible integer wavelet transforms", IBM Res.Rep., Comput.Sci./ Math., RC 21010, (October 22).

[10] V.Strela, P.N.Heller, G.Strang, P.Topiwala, C.Heil. 1999. "The application of multiwavelet filter banks to image processing", IEEETrans.Image Processing, vol.8, pp.548-563, (April 1999).

[11] X.Wu, K.U.Barthel, G.Ruhl.1998. "Adaptation to nonstationarity of embedded wavelet code stream", in Proc.Int.Conf.Image Processing, Chicago, IL, (October 1998).

[12] X.-G. Xia, J.S. Geronimo, D.P. Hardin, B.W.Suter. 1996. "Design of prefilters for discrete multiwavelet transform", IEEE Trans.Signal Proc., vol.44, pp.25-35, (January 1996).

[13] X.G.Xia, "A new prefilter design for discrete multiwavelet transform", IEEE Trans.Signal Processing, vol.46, pp.1558-1569, (June 1998).

[14] K.Nagamani, AG.Ananth.2011. "Analysis of SPIHT Algorithm for Satellite Image Compression", Advanced Computing International Journal, Vol.2, No.5, and (September 2011).

[15] Nagamani.K, AG.Ananth.2012. "Evaluation of SPIHT Compression Scheme for Satellite Imageries Based on Statistical Parameters", International Journal of Soft Computing and Engineering, ISSN: 2231-2307, volume-2, Issue-2, (May 2012).

[16] K.Rajakumar, T.Arivoli.2013. ''Implementation of Multiwavelet Transform coding for Lossless Image Compression'', an IEEE International Conference on Information Communication and Embedded systems, ISBN: 978-1-4673-5786-9. (February 2013).

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[17] Samir Kumar Bandyopadhyay, Tuhin Utsab Paul, Avishek Raychoudhury. 2011. ''Image Compression using Approximate Matching and Run Length'', an International Journal of advanced Computer science and applications.Vol.2, No.6, 2011.

[18] Prabhakar. Telagarapu, V.Jagannaveen, A.Lakshmi. Prasanthi, G. Vijaya Santhi.2011. ''Image Compression Using DCT and Wavelet Transformations'', International Journal of Signal Processing Image Processing and Pattern Recognition, Vol.4, No.3, (September 2011).

[19] Sachin Dhawan.2011. ''A Review of Image Compression and Comparison of its Algorithms'', IJECT, Vol.2, Issue-1, (March 2011).

[20] A.Razzaque, N.V.Thakur.2012. "Image compression and encryption: an overview", International Journal of Engineering Research and Technology, Vol.1.5, pp.1-7, (Jul.2012).Bowman, M., Debray, S. K., and Peterson, L. L. 1993. Reasoning about naming systems.