MAT JOURNALS
Journal of Image Processing and Artificial Intelligence
Volume 4 Issue 2

1d & 2d Signal Compression Using Discrete Wavelet Transform : A Survey

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Abstract
Today's smart world with high-speed communication devices demands elegant computing systems with lightening speed. Compression technology takes a major part in developing new generation computing systems. Popular applications like multimedia and medical data processing technology desires high data transmission rate, good perceptual signal quality and high compression rates. Wavelet based data compression techniques have advantages in lossless signal reconstructions and fit in dedicated data processing field. This paper highlights some wavelet transform based compression algorithms implementation and measuring performance towards quality of reconstruction and compression rate of one and two dimensional signal.

***Keywords**: Compression, Wavelet Transform, One and two dimensional wavelet compression, Peak Signal to Noise Ratio (PSNR), Compression Rate (CR).*

INTRODUCTION

Rapid development in science and engineering technology since from last few years is unimaginable because of new inventions of computational devices. Compression technology is also play a vital role in this growth, it boosts the chip designers to develop advanced designs with ne possible data compression algorithms [1-4]. There are several data compression algorithms efficiently working in real time applications. Signal compression is concerned with reducing the number of bits required to describe a signal to a prescribed accuracy [5]. Because compression is often a one of the preprocessing step applied to any kind of non-stationary signal produced by a source device such as a microphone, sensor, or camera. Either source signal is one dimensional signal like speech/audio signal or two dimensional signals like image [6-8]. In speech/image signal transmission through cables or internet needs compact coding of information in reduced number of bits with high transmission rate. This is possible by only two way, one by increasing the channel bandwidth another by using compression coding. Increase in bandwidth is more cost and it is not so preferable, so we us cost effective compression technology to increase the transmission rate [9].

Compression

Compression pronged towards eliminating redundant information with a good compression ratio and low bitrates and aimed to achieve

- Coding redundancy.
- Psychoacoustic/visual perception.

Compression algorithms categorized as lossy and lossless type coders. Lossless compression retains its all the information in a given signal, i.e., a decoder can perfectly reconstruct a compressed signal. In contrast, lossy compression eliminates information from the original signal. Model based coders are very complex and costly to implement and less perceptual quality, but achieves good compression rate. In time domain modulation coders are

somewhat fit for one dimensional but still suffer by signal quality [10, 11]. Hence we go for transform based coding to get better responses.
This paper highlights wavelet transform based compression method because of its versatile analysis procedure compared to other transforms.

Discrete Wavelet Transform (DWT)
Multiresolution representation for finite discrete sequence obtained by performing scaling and wavelet functions. Set of high pass and low pass filters converts signal into sequence of wavelet coefficients. For any discrete sequence S(n), n=0,1, 2, 3……… …M-1, DWT given by,

$$W(j,k) = W_{\emptyset}(j_0,k) + W_{\varphi}(j,k) \dots \dots \dots \quad (1)$$

where, $W_{\emptyset}$ is scaling function,

$$W_{\emptyset}(j_0,k) = \frac{1}{\sqrt{M}} \sum_{n} s(n) W_{\emptyset}(n) \dots \dots \quad \dots (2)$$

W_{ψ} is wavelet function,

$$W_{\varphi}(j,k) = \frac{1}{\sqrt{M}} \sum_{n} s(n) W_{\varphi}(n) \dots \dots \dots \quad ..(3)$$

J&K are scale and location index.
Similarly, inverse discrete wavelet transform (IDWT) reconstructs the wavelet coefficients into original signal[12],

$$s(n) = \frac{1}{\sqrt{M}} \left[\sum_{K} W_{\emptyset}(j_0,k)\, \emptyset_{j_0,k}(n) + \sum_{j=j_0}^{\infty} \sum_{k} W_{\varphi}(j,k) \varphi_{j,k}(n) \right] \dots \quad (4)$$

ONE DIMENSIONAL SIGNAL COMPRESSION USING WAVELET TRANSFORM
Speech signal is a form of one dimensional signal, its function varies with independent variable time and dependent variable as amplitude. Speech is a narrow band signal with frequency range is ≤ 8KHZ .while audio signal could be up to 20KHZ[13].
The DWT compression is carried out by neglecting the insignificant information and discarding them. It follows the steps

a) Wavelet decomposition: filtrate the input signal with set of high and low pass filters to generate approximate and detailed wavelet coefficients by selecting the wavelet function called as one level decomposition. Repeat the process if need more levels.
b) Wavelet compression: wavelet coefficients are scanned with fixed threshold values. There are two approach in threshold hard and soft, in hard threshold it retains coefficients above threshold value and remain coefficients are made zero.

$$T_{hard}(x) = \begin{cases} x, |x| \geq \lambda \\ 0, |x| < \lambda \end{cases} \dots \dots \quad .(5)$$

In soft threshold shrinks the coefficients to absolute values of threshold otherwise made zero

$$T_{soft}(x) = \begin{cases} x - \lambda, x \geq \lambda \\ x + \lambda, x \leq -\lambda \end{cases} \dots \dots \quad (6)$$

c) Psychoacoustic model: This model estimates the masking threshold of each scale by small power spectral density. First it calculates the sound pressure levels using spectrum and identifies the tonal and non-tonal signal in it and compute the masking function of each masker. By using absolute masking function it estimates the signal masking ratio (SMR).
d) Bit allocation and quantization: the coefficients obtained by wavelet compressor have frequency variations need quantization, but quantization levels depend on SMR of psychoacoustic model. Therefore at each quantization levels of wavelet coefficients SMR is required, it was governed by bit allocator [14].
e) Encoding: compressed coefficients through quantizer stored in wavelet vectors or encode by using consecutive

zero padding. For compactness use either Huffman or arithmetic encoding method.

f) Decoding: decode the encoded coefficients based on encoded pattern and de-quantize the coefficients.

g) Reconstruction: by using IDWT reconstruct the speech signal which retains the original signal [15].

This is effective method for wideband speech and audio signal compression using human auditory characteristic

TWO DIMENSIONAL SIGNAL COMPRESSION USING WAVELET TRANSFORM

Image are two dimensional signals with set of pixels arranged in an matrix form constitute by low and high frequency band as approximate and detailed information respectively, by adding them we get refined detailed image. Hence it is more importance to separate the low and high frequency information from image. This effective utilization of coefficient for compression possible by two dimensional wavelet transform [16].

There are different wavelet coding techniques for image compression they are

a. EZW(Embedded Zero wavelet)
b. SPIHT(Set Partition hierarchical tree)
c. SPECK(Set Partition embedded block coder)
d. WDR(Wavelet difference reduction)
e. ASWDR(Adaptively scanned WDR)

Embedded Zero Tree Coder (EZW):

It was the first progressive transmission algorithm introduced by J. Shapiro. Embed the signals with bit stream by means of truncation of zero's in prioritized order. The concept zero tree is to make insignificant coefficients and its descendants as zero and that kind of coefficients are called as 'zero node' or 'zero root'. Hence this method of compression called as embedded zero tree wavelet (EZW) coder.

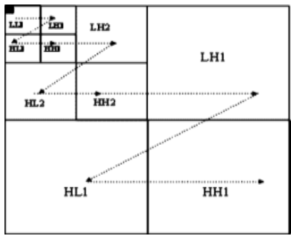

Fig.1 *EZW scanning.*

Decomposed coefficients are encoded in decreasing order of their band frequency. Pass these coefficients into multi-pass compressor by setting suitable threshold, if wavelet coefficients value is greater than threshold then encode it as refinement list otherwise to dominant list and allow them for next pass with new threshold. Repeat this process until get detailed image [17].

Set Partitioning Hierarchical Tree Coder (SPIHT)

Successive algorithm of EZW is SPIHT with best compression performance. The decomposed wavelet coefficients are ordered by coefficients most significant bit (MSB). The significance of coefficients determined by,

$$|C(i,j)| \geq 2^{n} \ldots \ldots \ldots \ldots \quad .(7)$$

Where, n={n_0,n_0-1,n_0-2,…………},i & j= set of coordinate.

Where, significance algorithm splits the set of pixels into partitioning subset T and test the magnitude of coefficients.

$$\max_{(i,j)\in T} \{|C(i,j)|\} \geq 2^{n} \ldots \ldots \ldots \ldots (8)$$

This partition creates new subset and once again tests the significance of subset. The encoder execution algorithm can be imitated by decoder by inverse operation of encoder. The function to identify the significance bit of encoder is given by,

$$S(\mathbb{T}) = \begin{cases} 1, & \max_{(i,j)\in T}\{|C(i,j)|\} \geq 2^{n} \\ 0, & otherwise \end{cases} \ldots \ldots .(9)$$

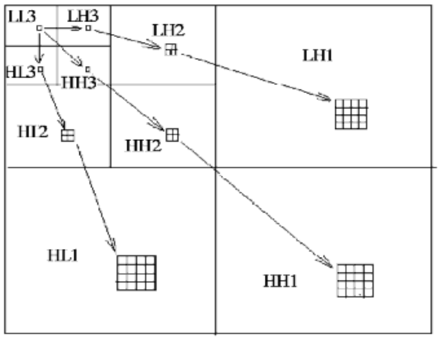

Fig.2: *root to descendent dependency in spatial domain.*

Above Figure shows how image pixels are divided into four band adjacent pixels as a node in hierarchical tree. Each node has either no offspring or a four offspring. Pixel in the highest level is called roots of tree with adjacent pixels. Partition of grouped pixels into subset is performed by sorting.

Majorly there is two major passes in SPIHT algorithm, they are sorting pass and refinement pass. In sorting pass with initialized list of insignificant point(LIP) by all roots, list of significant point(LSP) by zero and list of insignificant set (LIS) by descendants of node of only grand descendants. Start the sorting pass by scan list of LIP and LIS with updated sign bit and refinement pass succeeded by unscanned sorting pass by adding significant bits to the end of LSP with sign bits to recover ordered information then output the nth MSB of each |C(l,k)|. Efficiency can be increased by using entropy-coders but it creates coder more complex and expensive [18].

Set Partitioned Embedded Block Coder (SPECK)

The scalar quantized method, which exploits the relation between different frequency sub-bands as a block. It achieves frequency and spatial energy in hierarchical structure of transformed coefficients. This algorithm fallows bit-plane approach to successive approximation of wavelet coefficients. It performs significant pass to define significant states of each coefficients, if not calculates the magnitude with respect to threshold and in refinement pass produces successive approximation of already known to be significant bit. In each iteration threshold will be half and process repeats for next bit plane.

Consider an image under sub-band transformation, likely wavelet pyramidal decomposition. Topmost pixels are being a root. Size of set is 1 consist just 1pixel. There are two type of set partition, they are quad tree partition in Fig.4 and octave partition in Fig.5.

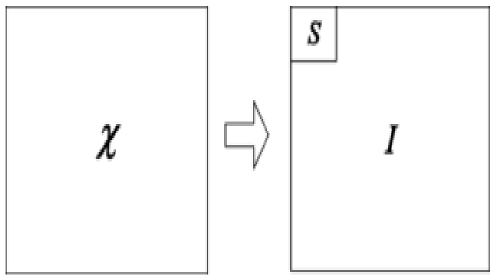

Fig.3: *Transformation of image 'x' to set 'S' and I.*

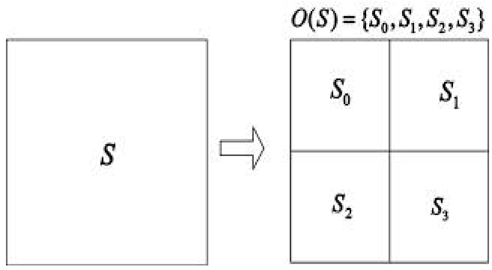

Fig.4: *Quad tree partition of set S.*

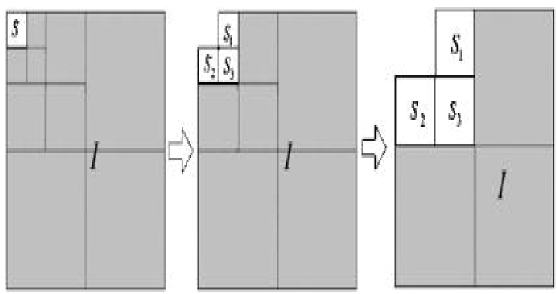

Fig.5: *octave partition of set I.*

Quad tree concentrated on zooming only area with high energy in set 'S' and code them. It codes the significance map with quad-tree a well-known method of spatial partition. In quad-tree partitioning, the significance state of an entire block of coefficients is tested and coded, the block is subdivided into four sub-blocks of approximately equal size, and the significance-coding process is repeated recursively on each of the sub-blocks. In octave, it exploits hierarchical pyramid structure of the sub-band decomposition, where it more likely that more energy is concentrated at the top most levels of the pyramid and one goes down the pyramid, energy content decreases gradually. In octave, set *I* is significant by some threshold n and it is more likely that pixel make *I* significant lie on the left region of the *I*. under decomposition gives set *S* .significance bits are grouped into small set and processed it . Insignificant bit are creates large set and undergoes partition into 4 off springs.

Decoder receives significant test results from coded bit stream by fallowing the same execution path of encoder. As with SPIHT, the SPECK algorithm stores set in implicitly sorted lists. Insignificant sets are placed in a list of insignificant sets (LIS). During the sorting pass, each insignificant set in an LIS is tested for significance against the current threshold. If the set becomes significant, it is split into four subsets according to the quad-tree decomposition structure described above. The four new sets are placed into an LIS, recursively tested for significance, and split again if needed. SPECK maintains multiple LIS lists in order to implicitly process sets according to their size. During the sorting pass, each time a set is split, the resulting subsets move to the next LIS. When a set is reduced in size to a single coefficient, and that coefficient becomes significant, then the singleton set is moved from its LIS to a list of significant pixels (LSP) for later processing in the refinement pass[19].

Wavelet Difference Reduction (WDR)

This algorithm follows SPIHT algorithm with one more added feature of implicitly locates the coefficients in a region of interest. By differenced reduction it identifies the significant wavelet transforms coefficients which need importance and enhance that value for high resolution. Compressed data operations are possible by algorithm of Wavelet difference reduction (WDR) of Tian and well [20]. During WDR coding the outputted significant pass consists of the signs of significant value along with sequence of bit which concisely describe the precise location of significant values.

It offers good perceptual quality and compression ratio, edge correlation and preservation. It suits for low resolution medical image at low BPP rate.

Adaptively Scanned Wavelet Difference Reduction (ASWDR)

The performance of WDR still has some room for improvement. The new algorithm ASWDR was introduced by walker [21]. This adaptive algorithm modifies the scanning order, which predicts the location of new significant values. If any coefficient be an significant for threshold, then succeeded coefficients predicted by half of the parent coefficient. This scanning order of ASWDR dynamically adapts to the locations of edge details in an image, and this enhances the resolution of these edges in ASWDR compressed images.

In some telemedicine applications data's need to transmit for a long distances demands high compression rate and bit-rate, this algorithm suits for such an application. Table (1) shows that ASWDR PSNR and BPP is comparatively good than SPIHT,WDR algorithms. Thus, ASWDR exhibits better perceptual qualities, especially at low bit rates, than WDR and SPIHT compressed images preserving all the features of WDR [22].

MEASURABLE METRICS

Mean Square Error (MSE):

$$\text{MSE} = \frac{1}{n\sum_{i=1}^{n}\text{error}^2} \ldots\ldots(10)$$

Where, n= signal length

Peak Signal to Noise Ratio(PSNR):

$$PSNR = 10\, log_{10}\,[R^2/MSE] \ldots\ldots(11)$$

Where R is bit stream of input signal.

Compression Ratio (CR):

$$CR = \frac{x}{x\prime} \ldots\ldots \quad .(12)$$

Where X=length of original signal, X'=length of compressed signal [19].

RESULTS AND DISCUSSIONS

One dimensional signal compression performance:

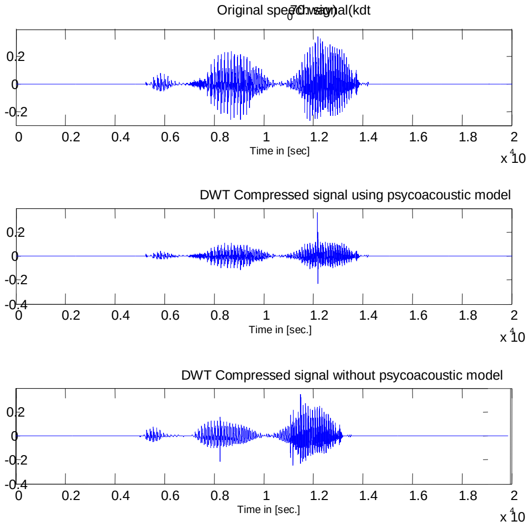

Fig.6: Reconstructed male speech signal using psychoacoustic model and without psychoacoustic model.

Table1: Audio compression response for male speech signal by haar, db4, sym2 wavelet family.

WAVELET FAMILY	LEVEL	PSNR	CR
Haar	1	75.31	0.827
	2	78.03	1.014
	3	78.54	1.034
Dabouchies4	1	75.43	0.834
	2	78.23	1.016
	3	78.61	1.032
Symlet4	1	75.36	0.830
	2	78.36	1.012
	3	78.31	1.028

Two dimensional signal compression performance

Table 2. *Two dimensional coder's performance for lena(256*256) for Db4 wavelet family .*

CODER TYPE	LEVEL	BPP	PSNR	CR(%)
EZTW	2	5.646	52.58	70.58
	3	5.121	52.51	64.02
	4	3.495	46.26	43.69
	5	1.307	35.46	16.34
SPIHT	2	3.312	39.54	52.5
	3	2.245	39.24	34.56
	4	1.021	35.67	22.56
	5	0.871	34.92	16.45
SPECK	2	3.513	39.40	43.98
	3	2.560	38.64	32.01
	4	0.940	33.69	11.75
	5	0.871	33.68	10.89
WDR	2	6.038	39.54	75.48
	3	5.798	39.87	72.49
	4	3.995	43.38	49.95
	5	2.562	39.38	32.03
ASWDR	2	5.768	39.54	72.11
	3	5.518	38.99	68.98
	4	3.829	43.55	47.87
	5	2,477	39.47	30.97

Fig.7 (a) *original Lena image is compressed by using (b)EZTW; (c)SPIHT; (d)SPECK; (e)WDR; (f)ASWDR.*

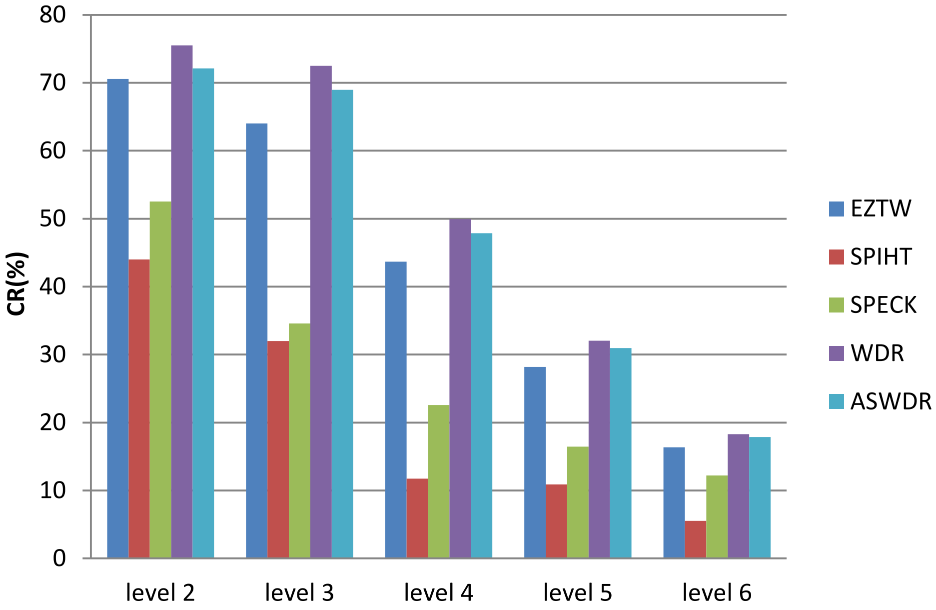

Fig 8. *CR response with levels.*

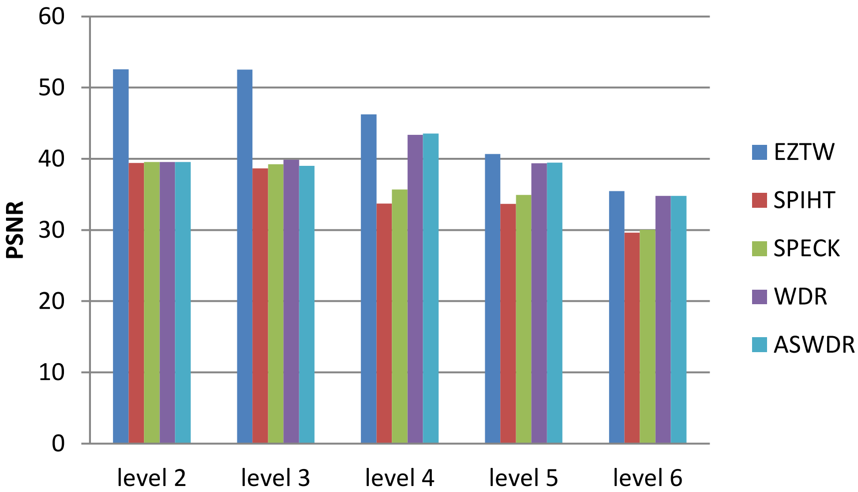

Fig 9. *PSNR response with levels.*

The above results show some uncertainty, in ASWDR coder CR is higher but poor PSNR values. EZTW coders PSNR is higher but poor CR. The above graph shows that PSNR and CR values are gradually decreases with increasing the number of levels.

CONCLUSION

This paper gives theoretical discussions of various wavelet based coding schemes of both speech and image processing. Each scheme found their own characteristic importance in specific applications. This data compression analysis is limited for db4 wavelet family, male speech signal and Lena (256*256) image datasets. It shows uncertainty in coder's performance made that still coding schemes need improvement in performance and demand for new better coder's developments.

REFERENCE

1. A. G. Ramakrishna and S. Saha, “ECG coding by wavelet-based linear prediction”, IEEE Trans. Biomed.

Eng., Vol. 44, No. 12, pp. 1253–1261, 1997.
2. Kinsner, W. and Langi, A. " Speech and Image Signal Compression with Wavelets", IEEE Wescanex Conference Proceedings, IEEE, New York, NY, 1993, pp. 368-375.
3. D. L. Donoho and I.M. Johnstone, "Ideal spatial adaptation by wavelet shrinkage," Biometrika, Vol. 81, No. 3: pp 425–455, 1994.
4. D. L. Donoho, "Denoising by soft thresholding," IEEE Transaction on Information Theory, Vol. 41, No. 3, pp 613-627, 1995.
5. A.N, Akansu, R.A. Haddad, "Multiresolution Signal Decomposition: Transforms, Sub bands, and Wavelets", Academic Press, ISBN 978-0-12-047141-6
6. Agbinya, J.I. "Discrete Wavelet Transform Techniques in Speech Processing", IEEE Tencon Digital Signal Processing Applications Proceedings, IEEE, New York, NY, 1996, pp 514-519.
7. R sudhakar,Ms R kartiga, S.Jayaraman,"Image compression using coding of wavelet coefficients-A survey"-.ICGST-GVIP journal Vol.5, No. 6, pp.34-36, 2005.
8. Jerome M Shapiro "Embedded image coding using zero tree of wavelet coefficients",IEEE transaction on signal processing,Vol. 41,No. 12, pp.3445-3462,1993.
9. Naveen kumar.R, B.N. Jagadale, J.S.Bhat, "Hybrid Image Compression using Modified Singular Value Decomposition and Adaptive Set Partitioning in Hierarchical Tree", Indian Journal of Science and Technology, Vol. 10 No. 28, pp. 1-9,2017.
10. Asad Islam &perman,"*An embedded and efficient low-complexity,Hierarchical image coder*",visual communication and image processing'99proceedings of SPIE,\.,Vol,3652,p294-305,jan.,1999.
11. J. Tian, R.O. Wells. " *A lossy image codec based in index coding*", IEEE Data Compression Conference, DCC'96, 1996, pp.456.
12. J.S. Walker, T.O. Nguyen. "*Adaptive scanning methods for wavelet difference reduction in lossy image compression* ",Proceedings of IEEE International Conference on Image Processing,vol.3, pp. 182-185, 2000.
13. Walker, J.S. A lossy image codec based on adaptive scanned wavelet difference reduction,ooptical engineering in press.
14. R.sudhakar,Ms R.Karthiga, S.Jayaraman-"image compression using coding of wavelet coefficients-A survey", ICGST_GVIP journal,Vol.5,No.6,pp.234-237, 2005.
15. A.N, Akansu, R.A. Haddad, "Multiresolution Signal Decomposition: Transforms, Sub bands, and Wavelets", Academic Press, ISBN 978-0-12-047141-6.
16. Naveen kumar.R, B.N. Jagadale, J.S.Bhat, "An Improved Neigh Shrink in Hybrid Wavelet Transform for Image Compression", International Journal in Advanced Research in computer Science, Vol. 8 No. 3, pp. 330-333,2017.
17. Shapiro, J. M., Embedded Image Coding Using Zerotrees Of Wavelet Coefficients. Ieee Transactions on Signal Processing, Vol. 41, No. 12 , pp. 3445-3462,1993.
18. Said, Amir; Pearlman, William A. "A new fast and efficient image codec based on set partitioning in hierarchical trees". IEEE Transactions on Circuits and Systems for Video Technology. Vol.**6**, No.3, PP. 243–250,1996.
19. Hsiang, S.T., Woods, J.W.: Embedded image coding using zeroblocks of subband/wavelet coefficients and context modeling. In: IEEE Int. Conf.

Circuits and Systems (ISCAS), vol. 3, pp. 662–665, 2000.
20. Naveen kumar.R, B.N. Jagadale, J.S.Bhat , "Use of Optimal Threshold and T-Matrix Coding in Discrete Wavelet Transform for Image Compression", IEEE sponsered , 3rd International Conference on Electronics and Communication System(ICECS-16), Vol. 3 No. 28, (2016) pp. 1462-1465.
21. Walker J.S., "Wavelet-based Image Compression. In Transforms and Data Compression Handbook", CRC Press LLC, Boca Raton, 2001.
22. Walker J.S., Nguyen T.O.," Adaptive Scanning Methods for Wavelet Difference Reduction in Lossy Image Compression". Proceedings of IEEE International Conference on Image Processing, Vol.3, pp.182−185, 2000.

