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Analyzing Impact of Wavelet Thresholding for Image Compression

Amandeep Kaur
R/S Electronics and Comm Engg Department
GZS Campus College of Engineering & Technology
Bathinda, Punjab, India

Dr Rakesh Kumar Bansal* and Dr Savina Bansal
Professors of Electronics & Communication Engineering
GZS Campus College of Engineering & Technology
Bathinda, Punjab, India

Abstract: Image compression plays a pivotal role in the applications of digital TV transmission, teleconferencing, remote sensing images, archiving medical images and multimedia communications. A digital image suffers from extensive storage and transmission resource requirements. Discrete Wavelet Transform technique has gained popularity owing to its ability of resolving less significant image details, thereby reducing size of an image. In this work, bi-orthogonal (bior1.3), reverse bi-orthogonal (rbio1.5) and discrete meyer wavelet (dmey) wavelets at various decomposition levels have been engaged to achieve compression. For truncation of wavelet transformed coefficients, images of true colour are tested against global and level dependent thresholding. A comparative analysis in terms of compression ratio, bits per pixel, PSNR and MSE is carried out using images from a text, facial and medical domains

Keywords: Image Compression, Wavelets, Thresholding, DWT, PSNR, MSE

I. INTRODUCTION

Compression lessens the size of data in a text, image or video, thus saving the storage space and transmission bandwidth. This is achieved as a result of image compression, which reduces the number of actual bits representing an image. Compression eliminates data irrelevancy and redundancy [1].The reduced file size leads to more image storage in a given amount of memory space. It also reduces the transmission costs, while reassuring quality of image. The increasing applicability of visual communication has given more precedence to the above issues. Accordingly efficient data compression techniques are essential for effective archival and faster image transmission, besides reducing the need of transmission channel capacity. This in turn helps in curtailing bandwidth for transmitting images over the internet, as uncompressed images consume more transfer time and memory space [2]. Compression has evolved as a technique to cut down the network traffic, cost along with transmission time and in turn improves system efficiency.

Image compression owing to its superiority and applicability has controlled the scene in spite of the fact that effective storage capacity and transmission bandwidth systems have also evolved during this period. Wavelet transforms decompose a given signal into various shifted and scaled versions of mother wavelet. During the decomposition process an image is divided into various sub-images. Wavelets have the unique advantage of being able to distinguish the fine details of signal. The sub-bands from transformed image contain the approximation and the detail parts of an image.

The main objective of this work is to critically examine image compression techniques and to apply DWT combined with thresholding methods for compressing different types of images. Performance comparison in terms of different performance metrics is done through Matlab simulations. The bi-orthogonal (bior1.3), reverse bi-orthogonal (rbio1.5) and discrete meyer wavelet (dmey) at various decomposition levels are used to achieve compression of a text, facial and medical image using level dependent and global thresholding. The related work and an overview of discrete wavelet transform and thresholding process specifically for image compression is presented in the next section. Subsequent sections include image details and performance comparison and presents overall discussions and conclusions.

II. RELATED WORK

Image compression involving wavelet transform and vector quantization along with psycho-visual features both in the frequency and space domains is proposed by many a researchers [1]. Wavelet transform acquires the decomposition of original image at various scales and subsequently vector quantizes and encodes the wavelet coefficients under the assumption that detail elements at high resolution are not visible to human eye and can be discarded to get compressed image [3]. DWT has also been used in embedded zero-tree wavelet algorithm proposed by **J. M. Shapiro** for image coding [4]. One possible solution to issue of thresholding wavelet coefficients in a transform based algorithm for still image compression is exhibited in. Processing data prior to quantization is also quite crucial particularly in higher compression ratio applications. It depends on local contrast and exploits wavelet localization properties along-with entropy maximization so as to locate an ideal threshold for the wavelet coefficients [5]. The usefulness of DWT over DCT for compression of images is well-established in literature [6], [7]. The appropriate selection of mother wavelet for image compression is suggested in [8], after examining effects of DWT on images classified on frequency basis. **R. D Aneja** *et al.* investigated the compatibility of modified bi-orthogonal filter (bior4.4) for image compression with level dependent and global thresholding techniques [9]. The selection of most efficient wavelet family for biomedical image compression is suggested by authors in [10] to produce satisfactory compression results and various types of biomedical images have been tested against a number of wavelet families. The well suited method for iris image compression is discussed by **A. Paul** *et al.* [11] which is dependent on wavelet transform.

III. DISCRETE WAVELET TRANSFORM

Wavelet transform provides the time and frequency domain representation of a signal. The wavelet transform is dependent on very small waves known as wavelets of limited duration and varying frequency [12]. Wavelet transform decomposes a given signal into various shifted and scaled versions of mother wavelet. During the decomposition process, image is divided into various sub-images as shown in Fig.1. Wavelets have the unique advantage of being able to distinguish the fine details of signal. The sub-bands from transformed image contain the approximation and the detail parts of an image. There are three types of details for each decomposition level namely, vertical details, horizontal details and diagonal details [6] The approximation part is comprised of low frequencies but the detailed parts have high frequencies, as these are analyzed using pairs of high pass and low pass filters. To reach the next level of decomposition the approximation part can be further decomposed and hence the signal can be compressed to the desired extent.

If decomposition is performed at higher level, then it is a great success to resolve important DWT coefficients from less important coefficients. The human visual system is insensitive to the removal of smaller details. The resulting sub-bands are labeled as LL (low-low) for coarse approximation, HL (high-low) for horizontal details, LH (low-high) for vertical details and HH (high-high) for diagonal details [13].

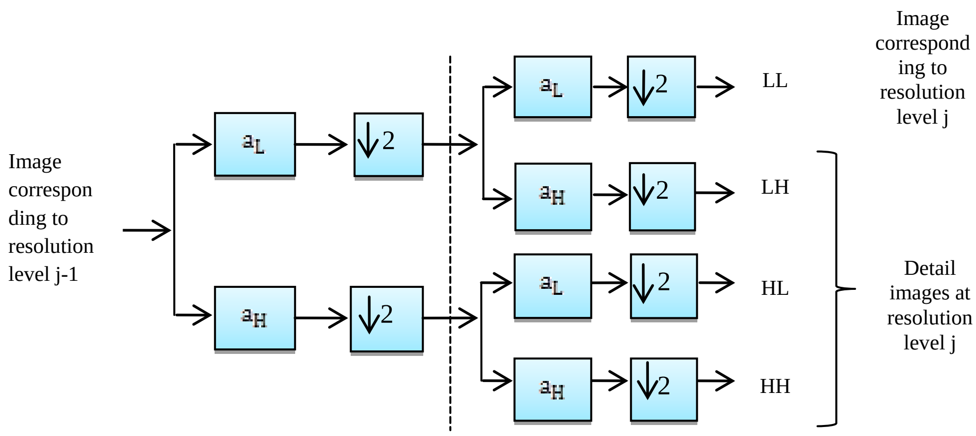

Fig.1: DWT based single level decomposition [14]

IV. THRESHOLDING

Image compression requires exclusively those wavelet coefficients which convey the major part of information. The energy compaction property of wavelet transform says that most of the signal energy is accumulated in few coefficients. In this way, we need to keep coefficients those having significant values and eliminate the remaining coefficients representing them as zeroes. The removal of small-valued coefficients can be achieved by setting all coefficients with values less than specific threshold value equivalent to zero [14]. There are two different ways of thresholding-

A. *Global Thresholding*

This technique implies that only one value of threshold can be applied inclusively to all wavelet coefficients obtained after the decomposition process and the insignificant coefficients can be discarded that have values less than threshold which means single value thresholds the entire image [14].

B. *Level Dependent Thresholding*

It implies that different threshold values are required for various sub-bands, and possibly is picked for each resolution level 'j'. In other words, local threshold may vary for different regions of an image. And the wavelet coefficients from each band are compared to the respective selected thresholds for discarding the less important details from a signal [14,15].

We have considered both techniques of thresholding in this work to analyze their impact on images from three different types of domains.

V. PERFORMANCE ANALYSIS

The effects of wavelet transform and thresholding techniques for compression are investigated using Matlab2013a platform. There are several steps involved in the whole process of image compression and their sequence is given below:

- Load an input image
- Select a wavelet type
- Then set the decomposition level for wavelet analysis
- Decompose the input image into sub images
- Next step is to select the thresholding and encoding method
- Compress the image

VI. PERFORMANCE METRICS

Performance metrics used for comparison in this work are:

A. *Compression Ratio (CR)*

It is the ratio of number of information carrying units in original image to that of encoded image. Its representation in percentage is given below:

$$CR\% = n2/n1*100 \quad (1)$$

n1 and *n2* is the number of information carrying units in original and encoded image respectively.

B. Bits PerPixel (BPP)

It gives the number of bits required to store one pixel of the image. Thus for the purpose of compression BPP should be less to reduce storage on the memory.

C. Mean Square Error (MSE)

It is a perceptual quality measure that represents the mean squared error between the original and compressed image. When the value of MSE goes down, it reduces the error.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m} \sum_{j=0}^{n} |X(i,j) - X_c(i,j)|^2 \qquad (2)$$

D. Peak Signal to Noise Ratio (PSNR)

It represents the ratio of peak signal power to peak noise power. Higher the PSNR, better is the quality of reconstructed or compressed image. When the value of PSNR is above 40dB then the two images are indistinguishable [16]. It is expressed in decibels.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad (3)$$

The images used include a text image, a face image and a medical image that are tested against the compression methods that utilize DWT, global and level dependent thresholding. In addition, *bior1.3, rbio1.5, dmey* wavelets are used to produce the images in compact form. The various 256x256 sized test images used in the present work are adopted from the literature and are given below:

(a) (b) (c)

Fig.2: Images tested against DWT compression (a) text image (b) facial image (c) medical image

VII. Experimental Results and Discussion

A. Comparison based on Compression Ratio

1) Text image:

The bits per pixel were kept fixed to 8 so as to reduce the image size atleast by two-thirds because original true color image has 24 BPP and the other parameters are recorded as follows:

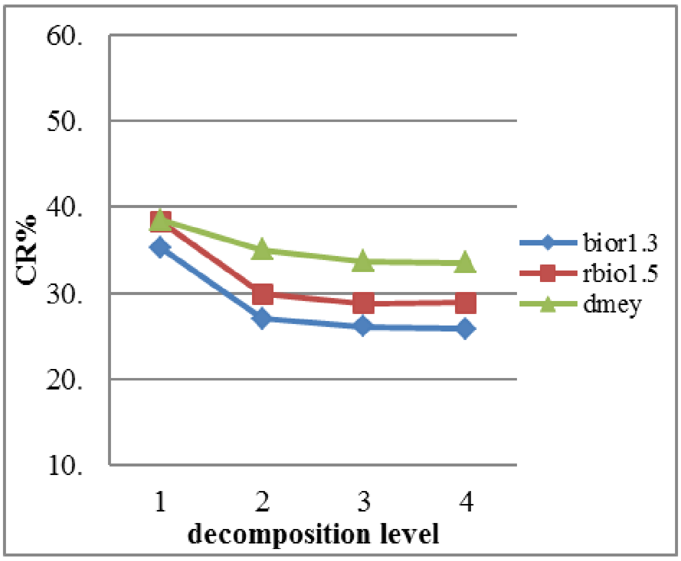

Fig.3: Compression results for text image using level dependent thresholding

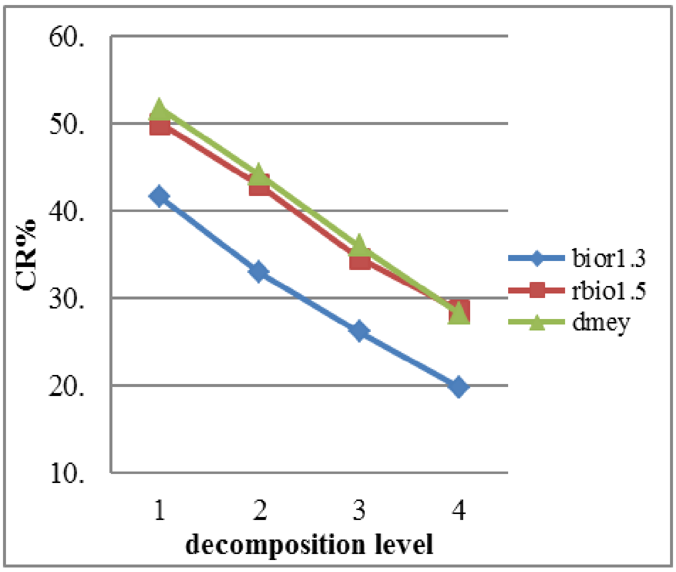

Fig. 4: Compression results for text image using global thresholding

From above observations it is clear that in case of each wavelet with the use of level dependent thresholding, size of image reduces with increase in decomposition level and becomes roughly stable after three decomposition levels. If we consider the global thresholding, image size continued to decrease with each decomposition level but it led to unacceptable degradation of image quality. It is observed that bior1.3 wavelet produced comparatively better results for text image.

2) Facial image:

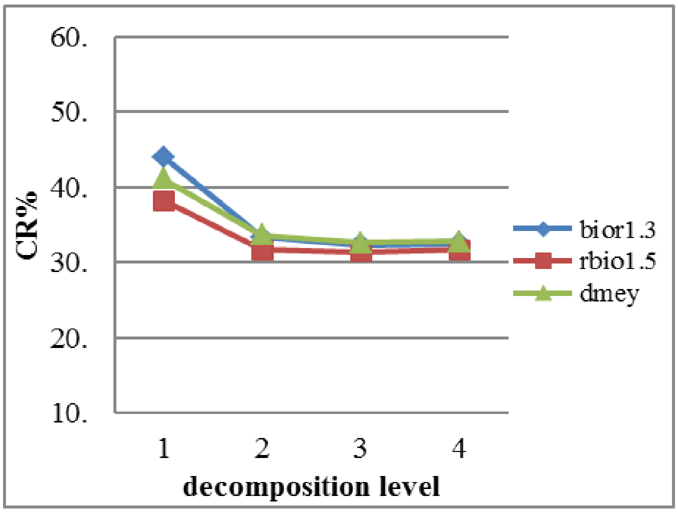

Fig.5: Compression results for facial image using level dependent thresholding

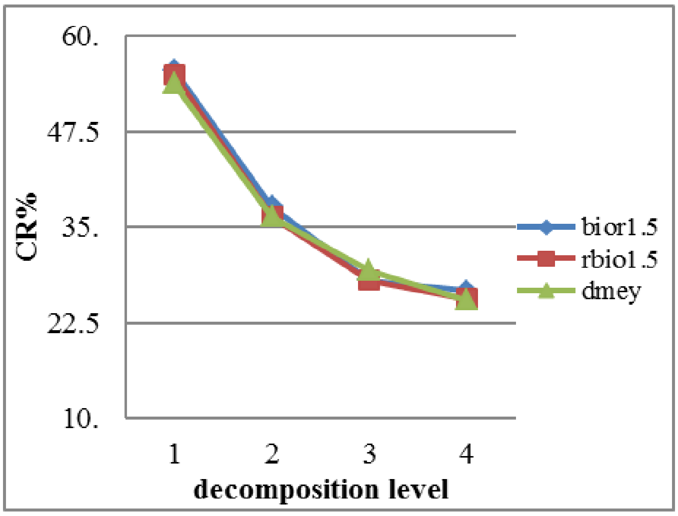

Fig.6: Compression results for facial image using global thresholding

After studying the effects of different wavelets for facial image, it is observed that image size decreases with each decomposition level in case of global thresholding but it becomes relatively stable after 2^{nd} level of level dependent thresholding. Overall observations made it clear that rbio1.5 produced better compression results for facial image.

3) Medical image:

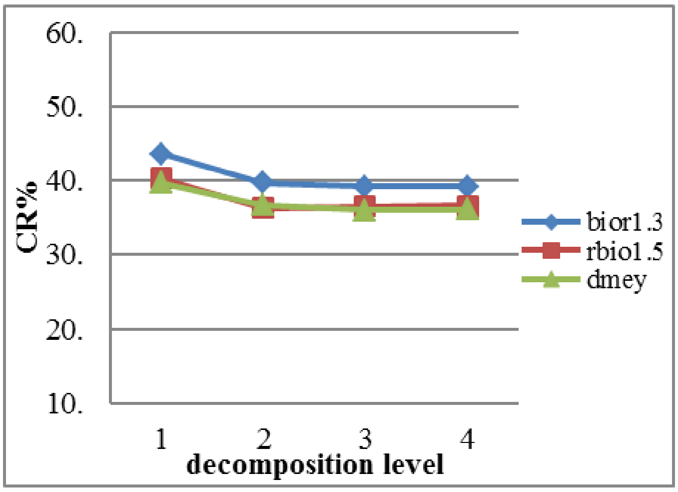

Fig.7: Compression results for medical image using level dependent thresholding

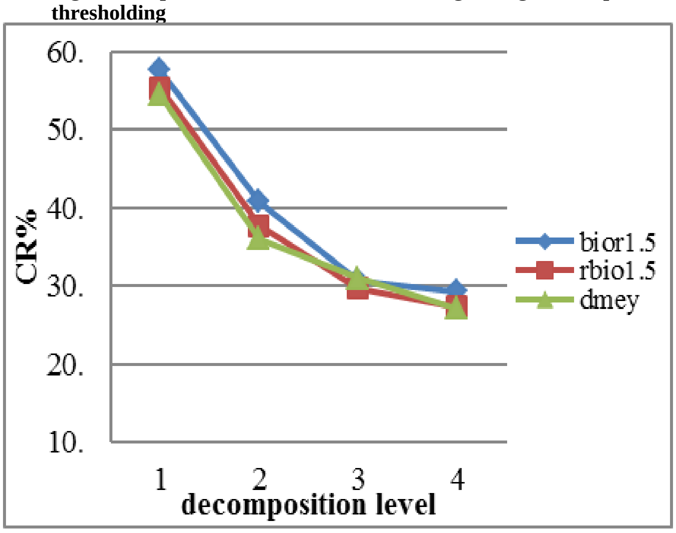

Fig.8: Compression results for medical image using global thresholding

For the case of medical image, it is seen that for level dependent thresholding, size of image decreased till second level and becomes stable for further decompositions. If we consider global thresholding, image is getting more and more compressed with the increase in number of decompositions. The dmey wavelet comes out with better performance for medical image.

B. PSNR Based Comparison

Level dependent thresholding is able to sustain the minimum PSNR with all three tested wavelets used in this work at any decomposition level as shown below in Table 1. Whereas, global thresholding is not good at maintaining minimum PSNR for any kind of image so quality loss is quite common using this method which can be seen in Table 2.

Table 1: PSNR comparison using level dependent thresholding

Wavelet	*Decomp. level*	*Level dependent thresholding*		
		Text image	*Facial image*	*Medical image*
Bior1.3	1	38.03	39.85	38.76
	2	38.09	41.76	40.45
	3	38.17	42.22	40.85
	4	**38.17**	**42.30**	**40.87**

Rbio1.5	1	40.26	42.15	42.09
	2	39.73	44.27	44.06
	3	40.48	44.78	44.50
	4	**40.67**	**44.91**	**44.60**
Dmey	1	39.91	42.58	42.59
	2	40.23	44.61	44.47
	3	40.31	45.13	44.86
	4	**40.37**	**45.25**	**44.94**

Table 2: PSNR comparison using global thresholding

Wavelet	*Decomp. level*	*Global thresholding*		
		Text image	*Facial image*	*Medical image*
Bior1.3	1	**40.59**	**42.68**	**40.98**
	2	32.76	37.43	36.73
	3	27.89	30.93	30.85
	4	22.13	24.20	24.77
Rbio1.5	1	**41.93**	**43.08**	**42.68**
	2	38.19	37.22	37.05
	3	32.71	30.65	30.55
	4	26.54	24.10	23.89
Dmey	1	**43.84**	**42.95**	**42.58**
	2	37.45	36.96	36.60
	3	31.97	30.10	29.96
	4	26.36	23.88	24.06

C. MSE Based Comparison

The impact of coefficient thresholding is also recorded in the form of MSE, its value decreases as the decomposition level increases for level dependent thresholding. But if global thresholding is considered, a sudden rise is seen in mean square error for each type of image at 4^{th} decomposition stage which indicates substantial quality degradation of an image.

Table 3: MSE comparison using level dependent thresholding

Wavelet	*Decomp. level*	*Level dependent thresholding*		
		Text image	*Facial image*	*Medical image*
Bior1.3	1	10.24	6.731	8.660
	2	10.08	4.340	5.862
	3	9.921	3.898	5.341
	4	**9.919**	**3.825**	**5.316**
Rbio1.5	1	6.126	3.966	4.015
	2	6.919	2.435	2.554
	3	5.828	2.163	2.307
	4	**5.567**	**2.101**	**2.253**
Dmey	1	6.633	3.587	3.584
	2	6.160	2.249	2.323
	3	6.049	1.994	2.123
	4	**5.973**	**1.942**	**2.086**

Table 4: MSE comparison using global thresholding

Wavelet	*Decomp. level*	*Global thresholding*		
		Text image	*Facial image*	*Medical image*
Bior1.3	1	**5.682**	**3.504**	**5.187**
	2	34.41	11.74	13.81
	3	105.7	52.5	53.42
	4	398.2	247.2	216.6
Rbio1.5	1	**4.173**	**3.20**	**3.511**
	2	9.873	12.32	12.83
	3	34.86	55.96	57.26
	4	144.2	252.8	265.6
Dmey	1	**2.686**	**3.299**	**3.593**
	2	11.71	13.09	14.23
	3	41.34	63.50	65.61
	4	150.4	266.2	255.2

VIII. CONCLUSIONS

Based on the results obtained for the tested images on the given set of wavelets, it is gathered that Level dependent thresholding method is more successful at resolving important details and the insignificant information at higher resolution levels without degrading the image quality to an unacceptable level. Global thresholding compresses the image without keeping an eye on the quality and results in depletion of image quality at higher levels of decomposition. Moreover, no wavelet performs optimally for all types of images. Based on these results, bior1.3 appears to be a more appropriate choice for text image, rbio1.5 for facial image and dmey for the medical image.

IX. REFERENCES

[1] M. Antonini, M. Barlaud, P. Mathieu and I. Daubechies, “Image coding using wavelet transform”, IEEE Transactions on Image Processing, Vol. 1, No. 2, pp. 205-220, Apr. 1992

[2] T. Bose, Digital Signal and Image Processing, John Wiley and Sons, Inc. 2004

[3] J. Akhtar, M.Y. Javed, “Image compression with different types of wavelets”, Proc. of 2nd International Conference on Emerging Technologies, pp. 133-137, Peshawar, Pakistan, Nov. 2006

[4] J.M Shapiro, Embedded Image Coding Using Zero-trees of Wavelet Coefficients. IEEE Transactions on Signal Processing Vol.41, no.12, pp.3445-3462, Dec. 1993

[5] M. G. Albanesi, “Thresholding wavelets for image compression”, Proc. of IEEE Compression and

Complexity of Sequences, pp. 374-389, Salerno, Italy, Jun. 1997

[6] S. Grgic, M.Grgic and B. Zovko-Cihlar "Performance analysis of image compression using wavelets", IEEE Transactions on Industrial Electronics, Vol. 48, No. 3, pp. 682-695, Jun. 2001

[7] I. Hacihaliloglu and M. Kartal, "DCT and wavelet based image compression in satellite images", Proc. of International Conference on Recent Advances in Space Technologies, pp. 79 – 84, Istanbul, Turkey, Nov. 2003

[8] G. K. Kharate, A. A. Ghatol and P. P. Rege, "Selection of mother wavelet for image compression on basis of image", Proc. of IEEE International Conference on Signal Processing, Communications and Networking, ICSCN, pp. 281-285, Chennai, India, Feb. 2007

[9] R. D. Aneja, S. Gupta and V. Batra, "An enhanced bi-orthogonal wavelet filter for image compression", International Journal of Computer Science and Communication, IJCSC, Vol.2, No.2, pp. 351-354, Jul-Dec, 2011

[10] V. Glaxo and P. Deepak, "Selection of wavelet families for biomedical image compression", International Journal of Engineering Research and Development, Vol. 5, Issue 6, pp. 8-14, Dec. 2012

[11] A. Paul, T. Z. Khan, P. Podder, R. Ahmed, M. K. Rahman and M. H. Khan, "Iris image compression using wavelets transform coding", Proc. of 2nd International Conference on Signal Processing and Integrated Networks (SPIN-2015), pp. 544-548, Noida, India, Feb. 2015

[12] A. Khatun and M. M. Hoque Chowdhury, "Image compression using discrete wavelet transform", International Journal of Computer Science Issues, IJCSI, Academic Journal, Vol. 9, Issue 4, No. 1, pp. 327-330, Jul. 2012

[13] A. Baviskar, S. Ashtekar, A. Chintawar, J. Baviskar and A. Mulla, "Performance analysis of sub-band replacement DWT based image compression technique", Proc. of IEEE India Conference (INDICON), pp. 1-6, Pune, India, Dec. 2014

[14] J. Abirami, K. Narashiman, S. Siva Sankari and S. Ramya, "Performance analysis of image compression using wavelet thresholding", Proc. of 2013 IEEE Conference on Information and Communication Technologies, pp. 194-198, Thuckalay, Tamil Nadu, Apr. 2013

[15] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", Pearson Education Inc., India, 2nd Edition, 2004

[16] https://www.mathworks.in/help/wavelet/compression.html