International Journal of Electrical, Electronics and Computer Engineering **6**(1): 139-144(2017)

ISSN No. (Online): 2277-2626

Image Compression using Wavelet Transform

Heema Sharma*, Shrish Dixit**, Babita Pathik and Dr. Shiv K. Sahu*******

**M. Tech. student, Department of CSE, LNCTE, Bhopal, (Madhya Pradesh), INDIA*

***Professor, Department of CSE, LNCTE, Bhopal, (Madhya Pradesh), INDIA*

****P.G. Coordinator, Department of CSE, LNCTE, Bhopal, (Madhya Pradesh), INDIA*

*****HOD Department of CSE, LNCTE, Bhopal, (Madhya Pradesh), INDIA*

(Corresponding author: Heema Sharma, heemasharma13@rediffmail.com)

(Received 27 April, 2017 Accepted 22 May, 2017)

(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Nowadays high quality of video or audio image capturing device has evolved which requires lots of storage space. So to lessen the storage space various image compression techniques has been developed. In this paper, a hybrid DWT and high boost filtering technique is presented. The simulation of proposed approach is done using MATLAB toolbox and comparative analysis is performed using performance metrics peak signal to noise ratio (PSNR), mean square error (MSE), root mean square error (RMSE) and signal to noise ratio (SNR). The comparative results of DWT-HBF is better in respect of all the metrics than DCT and DWT. Finally our proposed approach is better than the existing approach DCT and DWT.

Keywords: Image Compression, Lossy Compression, Lossless Compression, DCT, DWT, DWT-HBF

I. INTRODUCTION

This is the age of advanced digital technology which gives better quality and high resolution image but such images require lots of storage space which diminishes the performance of the network resources. Image compression is one of the widely used techniques which can greatly and effectively reduces the storage cost without losing the quality of image. The objective of an image compression system is to diminish the repetition of image data with a specific end goal to have the capacity to store or transmit data in a proficient shape. This outcomes in the decrease of document size and permits more pictures to be put away in a given measure of disk or memory space [1-3]. For lossy compression strategy, numerous standards have been produced, for example, JPEG [4] and JPEG 2000 [5] for still images. The remade image is not precisely same as the original image in lossy image compression strategy. A vital advancement in lossy compression is the foundation of the JPEG 2000 standard for compression of color images. Utilizing the JPEG2000 technique, a 24 bit/pixel color images can be diminished to between 1 to 2 bits/pixel, without clear visual antiquities.

The image compression technique is of two types: Lossless and Lossy compression. A high level of association exists between the neighboring pixels in natural images. In lossless compression methods, this statistical analysis are misused in such a way that the whole process is reversible i.e. the first picture is precisely recuperated. There is extensive enthusiasm for lossless strategies, particularly in applications which require high loyalty reproduced images (e.g. restorative imaging).

Similarly, in lossy compression systems for the most part result in a low compression ratio (typically 2 to 3). Henceforth, they are most certainly not utilized when a high pressure proportion is required. In lossy compression, the goal is to decrease the bit rate subject to a few requirements on the image quality. Generally lossy compression methods can be characterized into taking after classifications - perceptive coding, transform coding, wavelet/sub-band, vector quantization, fractal coding. The DWT is a change over the discrete Fourier change (DFT). DWT (Discrete Wavelet Transform) is sparser than DCT. Sparse element of the image is of incredible advantage standpoint to the compression procedure, seeking a proficient image of meager portrayal is a key idea of compression technology advancement. Wavelet transform [4] is a time domain analysis strategy for signals; it has the qualities of multi-determination investigation. At the same time, it can portray the local components of signals both in time domain and frequency domain. It is a time constraints localization technique with fixed window estimate yet factor shape, variable time window and frequency window. That is, in the low frequency area the frequency resolution and frequency zone, the frequency resolution and time resolution is low. Researchers have proposed a few enhanced strategies in view of wavelet change.

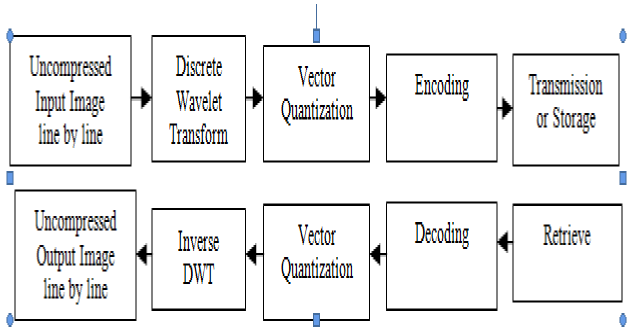

Fig. 1. Process of Image compression system.

Here we have registered a few codes in MATLAB for compression of images utilizing DWT. The outcomes have been seen in the research center for both the compression of gray scale and color images. The step by step process of image compression is shown in figure 1.

II. IMAGE COMPRESSION TECHNIQUES

Image data compression is classified into two different ways according to properties: lossless and lossy data compression.

A. Lossy Image Compression

In lossy image compression is the reconstructed image is not same as the original image, the image is close to the original one but not exact as the original image. This type of compression is suitable for those applications where small amount of loss of information is acceptable. Different types of lossy image compression method have been developed some of which are transform coding, vector quantization, fractal coding and block truncation coding.

Transform Coding. Transform coding is a common method for lossy image compression. It employs a reversible and linear transform to decorrelate the actual image into a set of coefficients in transform domain. The coefficients are then quantized and coded successively in transform domain. Several transforms are used in a range of applications. The discrete KLT (Karhunen-Loeve transform), which is based on the Hotelling transform, is most favorable with its information packing properties, but usually not practical since it is hard to work out. The DFT (discrete Fourier transform) and DCT (discrete cosine transform) fairly accurate the energy-packing efficiency of the KLT, and have further proficient implementation. In practice, DCT is used by the majority of practical transform systems since the DFT coefficients need two times the storage space of the DCT coefficients [6].

Vector Quantization. The basic idea in this technique is to develop a dictionary of fixed-size vectors, called code vectors. A vector is typically a block of pixel values. A given image is then partitioned into non-overlapping blocks (vectors) called image vectors. Subsequently, for all vector in the dictionary is determined and its index in the dictionary is used as the encoding of the original image vector. Thus, each image is represented by a sequence of indices that can be further entropy coded [7].

Fractal Coding. The essential idea here is to decompose the image into segments by using standard image processing techniques such as color separation, edge detection, and spectrum and texture analysis.

Then each segment is looked up in a library of fractals. The library essentially surrounds codes called iterated function system (IFS) codes, which are squashed sets of numbers [7].

Block Truncation Coding. In this scheme, the image is divided into non overlapping blocks of pixels. For each block, threshold and reconstruction values are determined. The threshold is typically the mean of the pixel values in the block. After that a bitmap of the block is derived by replacing all pixels whose values are greater than or equal (less than) to the threshold by a 1 (0). Then for each segment (group of 1s and 0s) in the bitmap, the reconstruction value is determined [7].

B. Lossless Compression Techniques

In lossless compression techniques, the original image can be perfectly recovered from the compressed image. These are also called noiseless since they do not add noise to the signal. It is also known as entropy coding since it use decomposition techniques to minimize redundancy.

Following techniques are included in lossless compression:

1. Run length encoding
2. Huffman encoding
3. LZW coding
4. Area coding

Run Length Encoding. This is a very simple compression method used for sequential data. It is very useful in repetitive data. This technique replaces sequences of identical pixels, called runs by shorter symbols. The run length code for a gray scale image is corresponding to by a sequence $\{V_i, R_i\}$ where Vi is the intensity of pixel and R_i refers to the number of consecutive pixels with the intensity V_i as shown in the figure. If both V_i and R_i are represented by one byte, this span of 12 pixels is coded using eight bytes yielding a compression ratio of 1: 5. (Fig. 2).

Huffman Encoding. As shown in Fig. 3, this is a general technique for coding symbols based on their statistical occurrence frequencies.

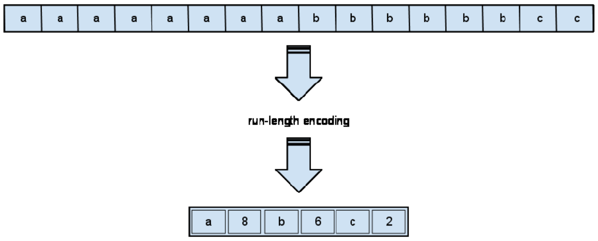

Fig. 2. Run-length encoding.

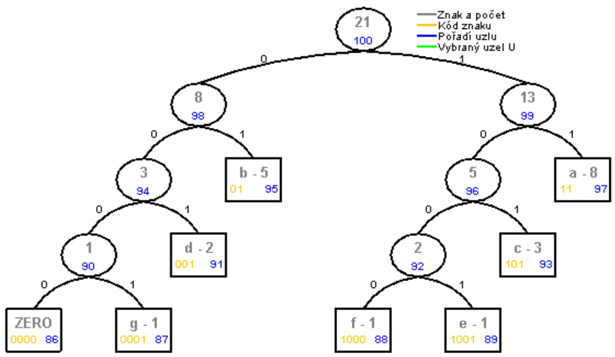

Fig. 3. Huffman encoding.

The pixels in the image are treated as symbols. The symbols that occur more frequently are assigned a smaller number of bits, while the symbols that occur less frequent are assigned a relatively larger number of bits. Huffman code is a prefix code. The binary code of any symbol is not the prefix of the code of any added symbol. Most image coding standards use lossy techniques in earlier stages of compression and use Huffman coding as the final step [10].

Area coding. Area coding [8] is an enhanced form of run length coding, which reflects the two dimensional character of images. It is a significant advancement over the other lossless methods. It does not make much of a meaning to interpret the coding of an image as a sequential stream, as it is in fact an array of sequences building up a two dimensional object. The idea behind this is to find the rectangular regions with the same characteristics. These rectangular regions are coded in a descriptive form as an element with two points and a certain structure. Area coding is highly effective and it can give high compression ratio but the limitation being non-linear in nature, which prevents the implementation in hardware.

LZW Coding. LZW (Lempel-Ziv–Welch) is a totally dictionary based coding. LZW encoding is further separated into static and dynamic. In static, dictionary is fixed during the encoding and decoding processes. In dynamic dictionary coding, the dictionary is updated if needed [9]. LZW compression replaces strings of characters with single codes. It does not perform any analysis of the incoming text. Instead, it just adds every new string of characters from the table of strings. The code that the LZW algorithm outputs can be of some arbitrary length, but it must have additional bits in it than a single character. LZW compression works best for files containing lots of repetitive data. LZW compression maintains a dictionary. In this dictionary all the stream entry and code are stored.

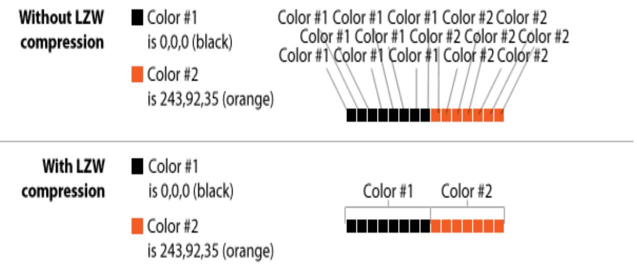

Fig. 4. Example of LZW coding.

III. PROPOSED METHODOLOGY

This section of the research work gives brief explanation about our proposed methodology for the reducing the storage cost of digital image which is the need of present scenarios. Compression of images is achieved by the removal of one or more of the basic data redundancies: such as spatial redundancy and frequency redundancy. In this we mainly focus on spatial redundancy.

Spatial Redundancy: Most of the image restrains correlated pixels. If the neighboring pixels are spatially correlated to each other, then it is known as spatial redundancy. In this thesis work, the spatial redundancy has been taken into consideration and data compression algorithm is analyzed by reducing the spatial redundancy.

1. *Multilayer Wavelet and Dual Tree Complex wavelet Transform (ML-DTCWT)*

The proposed methodology deals with the combination of multilayer wavelet and dual tree complex wavelet transform for image compression. The image compression technique proposed here is applicable to all standard grayscale digital images where high precision reconstructed image is required. In the proposed methodology, for image brightness and contrast has been enhanced and preserved using dominant brightness level analysis and adaptive intensity transformation. More specifically this approach first performs the DWT to decompose the input image into a set of band-limited components, called HH, HL, LH, and LL sub bands. Because the LL sub band has the illumination information [11], the log-average luminance is computed in the LL sub band for computing the dominant brightness level of the input image [12, 13] and filter also applied.

The LL sub band is decomposed into low-, middle-, and high-intensity layers according to the dominant brightness level. The adaptive intensity transfer function is computed in three decomposed layers using the dominant brightness level, the knee transfer function.

Huffman Coding. The Huffman coding is an entropy encoding algorithm which is used for lossless data compression.

It allows to the use of a variable-length code table for encoding a source symbol (such as a character in a file) where the variable-length code table has been derived in a particular way based on the estimated probability of occurrence for each possible value of the source symbol. It employs a explicit method for choosing the representation for each symbol, resulting in a prefix code that expresses the most common source symbols using shorter strings of bits than are used for less ordinary source symbols. The Huffman algorithm is based on statistical coding, which means that the probability of a symbol has an express bearing on the length of its demonstration.

After completing the layered process CWT apply check whether any information lost or not, if any information lost then revert it back otherwise process it for next iteration. The overall followed steps are:

1. Take a standard digital image and stored into variable (I).
2. Apply DWT into taken image.
3. Analyze Dominant brightness level on the basis of the LL band of DWT process.
4. Start decompositions on the basis of dominant brightness levels in to LL, LH, HL, HH sub bands.
5. Applying adaptive intensity transfer function into different intensity levels of the decomposed image and then smoothing the sub bands.
6. The smoothened image goes to the DTCWT.
7. Modify wavelet coefficients using and applying Kingsbury Q-filters.
8. Apply Huffman encoding to compress the modified coefficients images.
9. Stores the compressed image.
10. Now reconstruct the image using reverse process called Huffman decoding.
11. Apply high boost filter to enhance quality of reconstructed image
12. Inverse function of dual tree complex wavelet transforms ($DTCWT^{-1}$).
13. Store reconstructed image is in separate variable (out_I).
14. Calculate MSE (I, out_I), RMSE (sqrt(MSE)), PSNR (I, out_I), SNR(I_out, I).

Used comparison parameter is PSNR, MSE, RMSE and SNR of the image with a standard formula.

Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Peak Signal to Noise Ratio (PSNR)

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{peak}^2}{\mathrm{MSE}}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Root Mean Squared Error

$$RMSE = \sqrt{MSE} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

IV. EXPERIMENTAL RESULTS & ANALYSIS

In this section, the performance of our proposed method of image compression using modified SVM in spatial domain with high boost filter is deliberated. Experimental setting: computer frequency of 3.2 GHZ with 4 GB memory, Software Environment MATLAB 2012A. In the experiment, we compared the quality of reconstruction image. Simulation results are tested on five trained standard images such as Barbra, Baboon, cameraman and boat. Below is the compression of the tested images outcomes: each figure containing the four parallel processed output images where first image is an input original image therefore DCT, DWT and proposed DWT-HBF resulted images are shown and the comparative analysis of our method is done using well known performance measuring parameter such as MSE, RMSE, SNR and PSNR which are described below [14].

Mean Square Error (MSE): MSE is the quantity of error involving the original image and the compressed image. Mean Square Error is the cumulative squared error between the compressed image and the original image

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2$$

Peak Signal to Noise Ratio (PSNR): PSNR is the ratio of maximum power of the signal and the power of unnecessary distorting noise. Now the signal is the original image and the noise is the error in reconstruction. For a better compression the PSNR must be high.

$$PSNR = 20 \times \log_{10}\left[\frac{255}{\sqrt{MSE}}\right]$$

Table 1: MSE result for standard input image.

MSE comparison of DCT, DWT, DWT-HBF			
Method/Image	**DCT**	**DWT**	**DWT-HBF**
Lena	13.1477	7.0029	4.20142
Barbara	3.08036	1.4807	6.66621
Boat	11.6569	3.72092	1.23256
Cameraman	13.7442	3.13988	0.287481

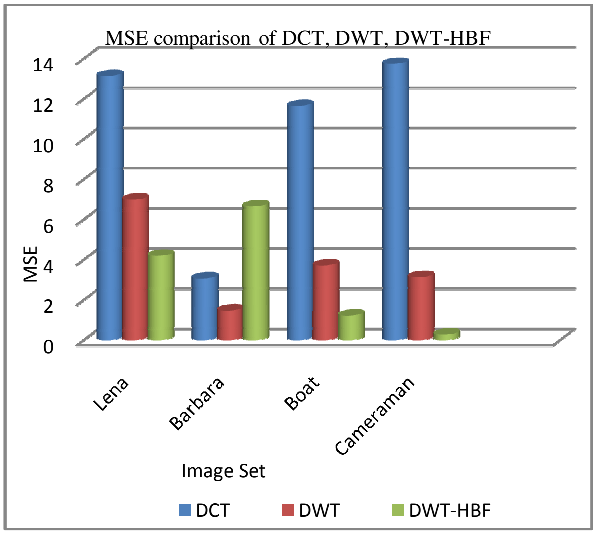

Fig. 5. Shows MSE comparison of DCT, DWT, DWT-HBF.

Table 2: RMSE result of standard input image.

RMSE comparison of DCT, DWT, DWT-HBF			
Method/Image	**DCT**	**DWT**	**DWT-HBF**
Lena	3.62598	2.6463	2.04974
Barbara	1.75509	1.21684	2.5819
Boat	3.41422	1.92897	1.11021
Cameraman	3.70731	1.77197	0.536173

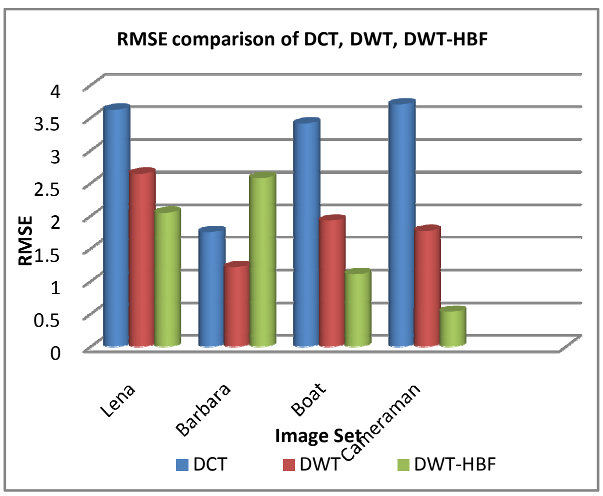

Fig. 6. Shows RMSE comparison of DCT, DWT, DWT-HBF.

The peak signal to noise ratio (PSNR) and signal to noise ratio (SNR) of our approach gives better than existing techniques illustrated in table 3, table 4 and result of this parameter is shown in figure 7 & 8.

Table 3: PSNR result for standard input image.

PSNR comparison of DCT, DWT, DWT-HBF			
Method/Image	**DCT**	**DWT**	**DWT-HBF**
Lena	33.8763	40.8251	47.5413
Barbara	32.3671	39.2765	46.4576
Boat	34.0896	42.1328	50.4202
Cameraman	33.7976	42.4839	53.8375

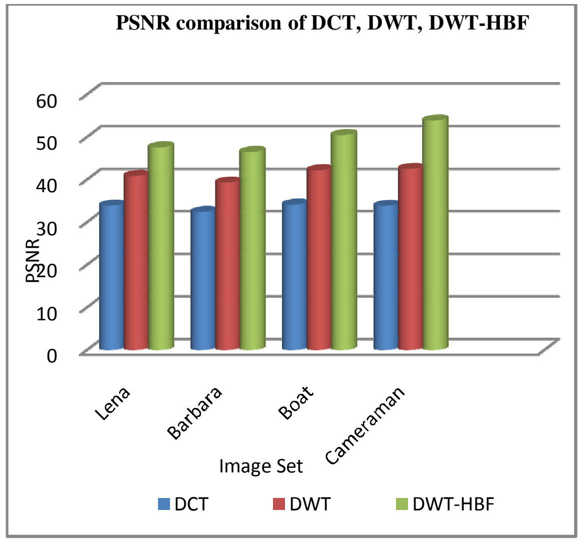

Fig. 7. Shows PSNR comparison of DCT, DWT, DWT-HBF.

Table 4: SNR result of standard input image.

SNR comparison of DCT, DWT, DWT-HBF			
Method/Image	**DCT**	**DWT**	**DWT-HBF**
Lena	3.5871	3.83238	3.63547
Barbara	2.82279	3.02933	3.03052
Boat	3.77642	4.69028	5.57361
Cameraman	3.56532	4.84674	8.50309

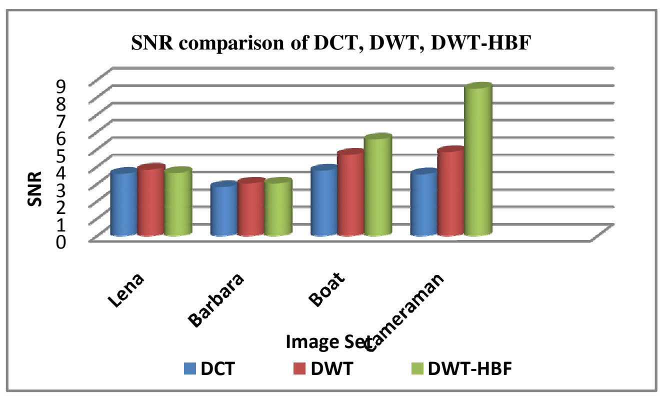

Fig. 8. Shows SNR comparison of DCT, DWT, DWT-HBF.

V. CONCLUSION

This paper, presented a hybrid DWT-HBF method for image compression method to utilize the advantages of both DCT and DWT techniques. The simulation results exposed that DWT yields an enhanced PSNR compared with that of DCT in image compression, when a number of coefficients used for image reconstruction is high. However when the number of coefficients is exceptionally small, DCT compression technique outperforms DWT technique. In addition, we have shown that the use of two thresholds advance the compression of DWT technique, this technique is named DWT-HBF proposed. The DWT-HBF gives better PSNR, MSE, RMS and SNR than DCT and DWT. Lastly, it is revealed that the DWT, DCT technique, a hybrid method, which is the combination of DCT, DWT and HBF presents better PSNR comparing to DCT technique for all transform coefficients used in image reconstruction but comparing to hybrid DWT-HBF, this technique presents better PSNR only when transform coefficients are below 18%.

REFERNCES

[1]. M. Mozammel Hoque Chowdhary and Amina Khatun, “Image Compression Using Discrete Wavelet Transform”, *lJCSI International Journal of Computer Science Issues,* Vol. **9**, Issue 4, No I, PP, 327- 330, July 2012.

[2]. Pratik Chavada, Narendra Patel, and Kanu Patel, Region of Interest Based Image Compression, *International Journal of Innovative Research in Computer and Communication Engineering,* Vol. **2**, Issue 1, PP2747-2754, January 2014.

[3]. Mohammed Abo-Zahhad, Sabah M. Ahmed and Nabil Sabor, “Wavelet Threshold Based ECG Data Compression Technique Using Immune Optimization Algorithm”, International Journal of Signal Processing, *Image Processing and Pattern Recognition,* Vol. **8**, No. 2 (2015), pp. 347-360.

[4]. R. C. Gonzalez and R. E. Woods, “Digital Image Processing”, Second edition, pp. 411-514, 2004.

[5]. N. Ahmed, T. Natarajan, and K. R. Rao, "Discrete cosine transform," *IEEE Trans. on Computers*, Vol. **C-23**, pp. 90-93,1974.

[6]. Mr. T. Sreenivasulu Reddy Ms. K. Ramani Dr. S. Varadarajan Dr. B.C. Jinaga, “Image Compression Using Transform Coding Methods”, *International Journal of Computer Science and Network Security*, VOL. **7** No.7, July 2007.

[7] Yang and Bourbakis, “An Overview of Lossless Digital Image Compression Techniques,” *Circuits & Systems, 2005 48th Midwest Symposium*, vol. **2** *IEEE*, pp 1099-1102,7–10 Aug 2005.

[8]. T. Rammohan, K. Sankaranarayanan, “An Efficient Image Compression Technique with Scalar Quantization Through Wavelet-based Contourlet Transform with Modified SPIHT Encoding”, *In proceeding of IEE Explore.*

[9]. Yuancheng Li; Qiu Yang; Runhai Jiao; "A Novel Image Compression Algorithm Using the Second Generation of Curvelet Transform and SVM", WRI Global Congress on Intelligent Systems, GCIS '09, Volume **3**, Page(s): 117 - 121,2009.

[10]. Ridhi Jindal “A Review on Recent Development of Image Compression Techniques”, *International Journal of Advance Research and Development*, 2017 Volume**1**, Issue1.

[11]. H. Demirel, C. Ozcinar, and G. Anbarjafari, “Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition,” *IEEE Geosci. Reomte Sens. Lett.*, vol. **7**, no. 2, pp. 3333–337, Apr. 2010.

[12]. E. Reinhard, M. Stark, P. Shirley, and J. Ferwerda, “Photographic tone reproduction for digital images,” in *Proc. SIGGRAPH Annu. Conf. Comput. Graph.*, Jul. 2002, pp. 249–256.

[13]. S. Chen and A. Beghdadi, “Nature rendering of color image based on retinex,” in *Proc. IEEE Int. Conf. Image Process.*, Nov. 2009, pp. 1813–1816.

[14]. Vijayshri, C. and S. Ajay, Review of a novel technique: Fractal image compression. *Int. J. Eng. Technology* - 2010, **1**(1): 53-56.