ISSN 2229-5518

Image Compression using Wavelet and Ridgelet Transform

Sukh Singh Ahirwar, Prof. Abhishek Jain, Prof. Sheena Kumar

Abstract—In real time applications, image compression plays a very important role in efficient storage and transmission. At present, many transform based compression techniques are developed and utilized. Aim of this paper is to evaluate and analyze Image Compression Techniques using Discrete Wavelet Transform and Ridgelet Transform. The performance parameters such as Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR) and Root Mean Squared Error (RMSE) are evaluated based on the algorithms for several standard colored images. The simulation result shows that both the techniques provide sustain faithful compression and reproduction of the images, preserving the quality of the images.

Index Terms— Wavelet Transform, Ridgelet Transform, PSNR, RMSE, Image Compression.

---

1 Introduction

IMAGE compression means reducing the volume of data for representing an image. The main aim of image compression is to reduce both spatial and spectral redundancy to store or transmit data in a proper manner. After the compression of an image, it is reconstructed at the receiver to reproduce the original image.

The need for an efficient storage and transfer of medical data is dramatically increasing [1]. The aim of compression is to reduce bit rates for communication and to achieve lower data archiving while having an acceptable image quality. Different compression methods have been proposed for medical images earlier based on JPEG and DCT [2]. However, DWT has been the most successful in achieving higher compression ratio [3]. The 2-D discrete wavelet transform is a separable transform that is optimal at isolating the discontinuities at horizontal and vertical edges. In two-dimensional DWT, a signal passes through low pass and high pass analysis filter banks followed by a decimation operation, along x-dimension and y-dimension separately. Finally, the image has been broken into four bands. The JPEG 2000 is the image compression standard based on DWT. This provides better performance than JPEG for high resolution images.

A new multi-resolution transform was developed by Candés and Donoho in 1999 [4] known as Ridgelet Transform (RT) to overcome the drawbacks of wavelet transform. The transform was introduced as a sparse expansion for function on continuous spaces that are smooth away from discontinuities along line. The Ridgelet transform is optimal to find only lines of the size of the image.

Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves. In such condition the Ridgelet Transform gives better performance [4], [5].

2 Wavelet Transform

Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function (t) as a superposition of a set of such wavelets or basic functions [5]. These basic functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilation and translation operation. Discrete Wavelet Transform of a finite length signal s(n) having N components, for image is expressed by an N x N matrix [6], [7].

2.1 Wavelet Filter Decomposition and Sub- Band Coding

For the designing of filters, sub-band coding is used. Sub-band coding is a coding strategy that tries to isolate different characteristics of a signal in a way that collects the signal energy into few components [7]. This is referred to as energy compaction. Energy compaction is desirable because it is simply to efficiently encode these components than the signal. The most commonly used implementation of the discrete wavelet transform (DWT) consists of recursive application of the low-pass/high-pass one-dimensional (1-D) filter bank successively along the horizontal and vertical directions of the image [8], [9]. The low-pass filter provides the smooth approximation coefficients while the high-pass filter is used to extract the detail coefficients at a given resolution.

Both low-pass and high-pass filters are called sub-bands. The number of decompositions performed on original image to obtain sub bands is called sub-band decomposition level. The high pass sub-band defineds residual information of the original image, needed for the perfect reconstruction of the original image from the low-pass sub-band while the low pass sub-band represents a down sampled low- resolution version of the original image. It is widely used for computer and human vision, musical tone generation, finger print compression etc.

The filtering step is followed by a sub-sampling operation that decreases the resolution from one transformation level to the other. After applying the 2-D filler bank at a given level n, the detail coefficients are output, while the whole filter bank is applied again upon the approximation image until the desired maximum resolution is achieved. Fig.1. shows wavelet filter decomposition.

ISSN 2229-5518

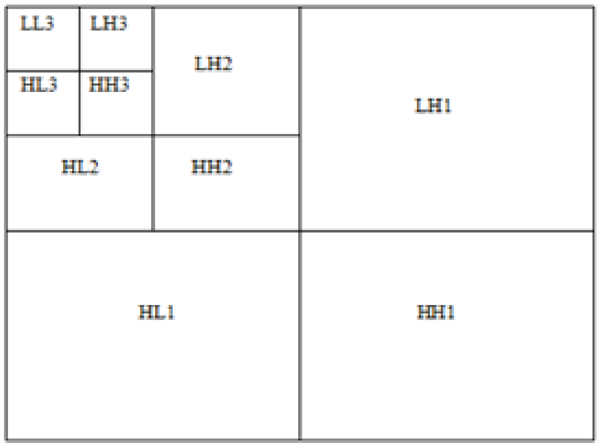

Fig. 1. Wavelet Filter Decomposition

The sub-bands [10-11] are labeled by using the following symbols:

1. LLn is the approximation image at resolution (level decomposition) n, resulting from low-pass filtering in the Vertical and Horizontal directions.

2. HLn is defined the Vertical details at resolution n, and results from Vertical low-pass filtering and Horizontal high-pass filtering.

3. LHn defined the Horizontal details at resolution n, and results from Horizontal low-pass filtering and Vertical high-pass filtering.

4. HHn defined the diagonal details at resolution n, and results from high-pass filtering in both directions.

3 Ridgelet Transform

The performance of wavelets is mainly due to the good performance for piecewise smooth functions is 1-dimension, unfortunately such is not the case in 2-dimensional.

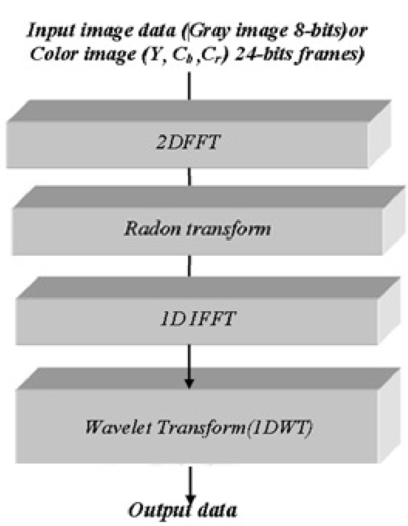

Fig. 2. Schematic diagram of Ridgelet transformation

W the properly of the WT that most image information is contained in a small number of significant coefficient, around the location of singularities or image edge. Therefore, new image process scheme called RT which is based on true 2-dimensional transform are expected to improve the performance over the current WT [9-12]. This transform is computed using the procedure and flowchart given in Fig.2.

It needs the computation of Fast Fourier Transform (2D-FFT) first and then the application of randon transform. After that the data will be treated as 1-Dimensional information hence, the 1D Inverse Fast Fourier Transform (IFFT) will be applied [13-14]. The Ridgelet computation requires further the application of 1-Dimension wavelet transform to the resultant data. The final coefficient obtained from the previous step will be called the Ridgelet coefficients. These in turn require the following main steps: Ridgelet steps are as given below-

1. Cartesian to polar conversion uses an interpolation scheme, which requires the substitution of the sampled values of the Fourier transform, where the points fall on lines through the origin.

2. Perform the 1-dimensional Inverse Fast Fourier Transform (IFFT) on each line; i.e., for each value of the angular parameter.

3. The (IFFT) is calculated along each radial line followed by a 1-D wavelet transform which uses this strategy in connection with Ridgelet Transform [14].

4 Methodology

The flowchart in Fig. 3 shows the sequence of the steps involved in image compression.

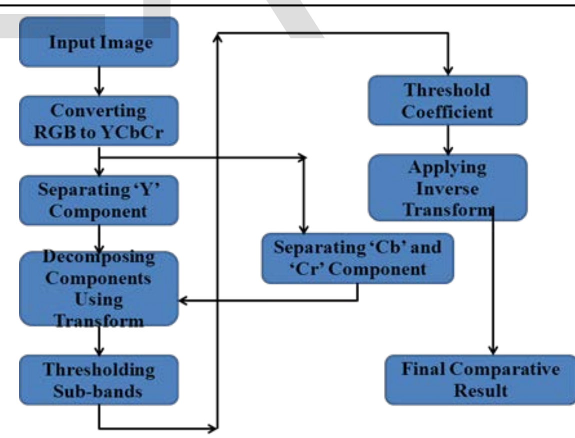

Fig. 3. Image compression using Ridgelet and Wavelet Transform

The stepwise techniques for image compression using Wavelet and Ridgelet Transforms [15] are:

4.1 Using Wavelet Transform

Step 1: Convert input image from RGB to YCbCr Format.
Step 2: Separate the components Y, Cb, Cr.
Step 3: Process Y component.
3.1: Decompose Y component using discrete wavelet
3.2: Threshold subbands –a and h, v, d at all levels.
For a subband s(i, j), the threshold value,

ISSN 2229-5518

(i) 1*m for a3,
(ii) 2*m for h3, v3, d3
(iii) 3*m for h2, v2, d2 and
(iv) 4*m for h1, v1, d1.

Step 4: Apply inverse wavelet transform to threshold coefficient matrix - wth to get the reconstructed image component Y.

Step 5: Repeat steps 3 and 4 for Cb and Cr components.

Step 6: Calculate MSE and PSNR between original and reconstructed image.

4.2 Using Ridgelet Transform

Step 1: Transform input image from RGB to YCbCr format.
Step 2: Separate the components Y, Cb, Cr.
Step 3: Process the Y component.
3.1: Decompose Y component using ridgelet.
3.2: The multiplier values used for
The subbands-
(i) 1*m for the most significant band 1(at level 3)
(ii) 2*m for band 2
(iii) 3*m for band 3
(iv) 4*m for band 4
3.3: For Ridgelet Transformed coefficient matrix of a subband is r(i, j), threshold value for column j,

$$v(j) = multiplier * \frac{1}{row} \sum_{i=1}^{row} r(i,j) \tag{1}$$

Step 4: Invert the image from thresholded coefficient matrix - rth to get reconstructed Y component.

Step 5: Repeat steps 3 and 4 for Cb and Cr components.

Step 6: Calculate MSE and PSNR between original and reconstructed image.

5 Performance Parameters

5.1 Mean Square Error (MSE)

It is a measure of the distortion for lossy compression. Mean square Error between two images is given as[16],[17],

$$MSE = \frac{1}{K} \sum_{i=1}^{k} (P_i - Q_i)^2 \tag{2}$$

Where, Pi is original image, Qi is compressed image data and k is the size of image.

5.2 Root Mean Square Error (RMSE)

It can be define as the square root of the MSE.

$$RMSE = \sqrt{MSE} \tag{3}$$

5.3 Peak Signal to Noise Ratio (PSNR)

This is another measure of the signal quality. This can be given by the formula shown below:

$$PSNR = 20 \log_{10} \left(\frac{max|P_i|}{RMSE} \right) \tag{4}$$

5.4 Compression Ratio (CR)

This is the parameter which is measure of number of original image divided by compressed image.

$$CR = \frac{original\ image}{compressed\ image} \tag{5}$$

6 Results & Observations

We have implemented the algorithms using MATLAB 13. We have checked our results for the various images. Here the results are shown for two common images.

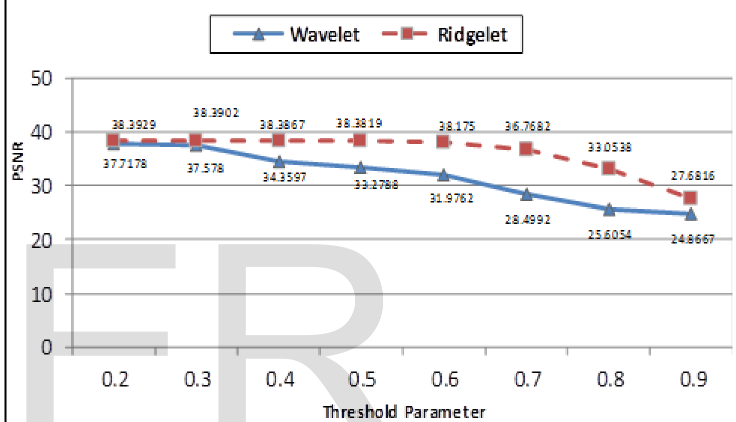

Fig. 4. Graph between the PSNR and Thresholding parameter (TP) for the Peppers.png

0.6	9.4044	31.9762	25.8636	3.3709	38.1750	8.9003
0.7	10.8561	28.4992	27.0916	4.7337	36.7682	10.8429
0.8	13.6526	25.6054	33.4712	7.2839	33.0538	14.9467
0.9	14.6390	24.8667	37.9311	10.6165	27.6816	21.1568

ISSN 2229-5518

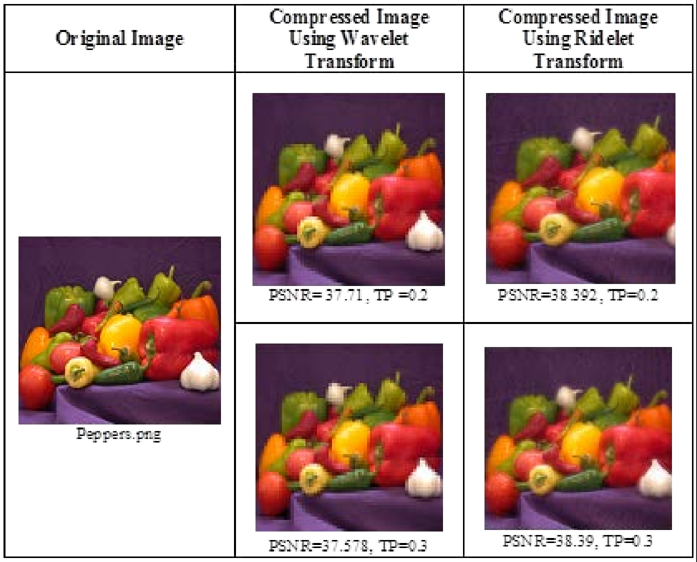

Fig. 5. Original and compressed images using Wavelet transform (WT) & Ridgelets transform (RT)

TABLE 2
RESULTS FOR THE SECOND IMAGE (BIRD2.PNG)

Thresolding Parameter (TP)	**Wavelet Transform**			**Ridgelet Transform**		
	RMSE	*PSNR*	*(CR)*	*RMSE*	*PSNR*	*(CR)*
0.2	2.1919	43.7212	1.0137	3.0772	41.2324	1.9131
0.3	3.5363	42.1405	15.9189	3.0777	41.2298	5.9121
0.4	4.8232	41.1901	17.3235	3.0780	41.2273	7.9130
0.5	7.3831	39.9238	22.6538	3.1888	41.1023	9.9074
0.6	8.3223	36.6645	28.0476	4.2987	40.1250	12.8586
0.7	8.7045	33.8819	29.4501	5.6482	39.2794	14.9188
0.8	12.4140	27.1679	32.7222	6.4319	38.8837	16.6163
0.9	15.6897	24.2205	53.5454	7.3678	35.0769	32.3118

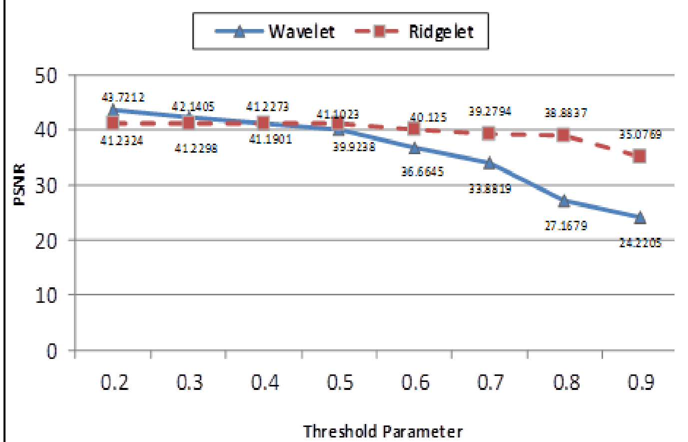

Fig. 6. Graph between the PSNR and Thresholding parameter (TP) for the Bird2.jpg

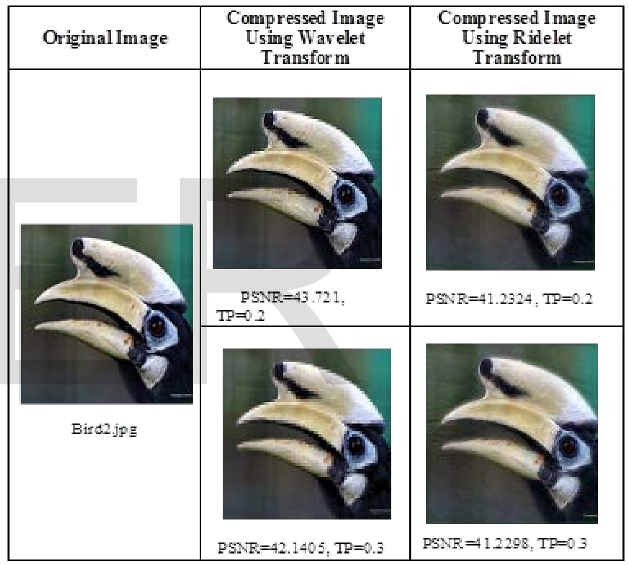

Fig. 7. Original and compressed images using Wavelet transform (WT) & Ridgelets transform (RT)

From the tabulated and graphical results shown in Table 1, Table 2, Fig. 4, 5, 6 and 7 for both the images, we can see that the PSNR is higher for image compressed using ridgelet transform as compare to the image compressed using wavelet transform for the higher value of P which corresponds to the lower value of percentage coefficients. Apart from this, from the compressed images given in the results we can observe that the images have more information preserved in it when those are compressed using ridgelet transform as compared to wavelet transform.

4 CONCLUSION

Simulation results show that performance parameters RMSE is slightly lower and PSNR is slightly higher for Ridgelet Transform whereas Compression Ratio (CR) is much higher in Wavelet Transform. By simulation results we can conclude

ISSN 2229-5518

that both techniques have their specific properties. For higher transmission performance and increased storage space, Wavelet Transform can be preferred whereas when image quality is the major concern then Ridgelet Transform can be preferred.

REFERENCES

[1] E.J. Candes, Ridgelets, Theory and Applications, Ph.D. Thesis, Aug.1998, Department of Statistics, Stanford University.

[2] E.J. Candes, Laurent Demanet, D.L. Donoho, Lexing Ying, "Fast Discrete Curvelet Transforms", Stanford University Press Notes, July 2005.

[3] Candµes, E. J., Monoscale ridgelets for the representation of images with edges, Technical Report, Statistics, Stanford, 1999

[4] Nilima D. Maske, Wani V. Patil, "Comparison of Image Compression using Wavelet for Curvelet Transform & transmission over Wireless Channel" International Journal of Scientific and Research Publications, Volume 2, Issue 5, May 2012 1 ISSN 2250-3153.

[5] Gonzalez, Woods, Eddins, Digital Image Processing (Pearson Education, 2008).

[6] David Salomon, Data Compression, The Complete Reference, Reprint, Springer Verlag, 2nd Edition, 2001.

[7] R.Sudhakar, Ms R Karthiga, S.Jayaraman, "Image Compression using Coding of Wavelet Coefficients - A Survey", ICGST GVIP Journal , Vol 7, 2007.

[8] Abhishek Jain & Dr. Ashutosh Datar, "Spatial Video Compression using EZW, 3DSPIHT, WDR & ASWDR Techniques" International Journal of Advanced Research in Computer Science and Software Engg. 3 (7), July 2013, Vol. 3, Issue 7, pp. 1-9.

[9] Negar Riazifar, and Mehran Yazdi Effectiveness of Contourlet vs Wavelet-Transform on Medical Image Compression: a Comparative Study World Academy of Science, Engineering and Technology 25 2009

[10] Joshi. M., Manthalkar, R., Joshi, V. "Color Image Compression Using Wavelet and Ridgelet Transform", Seventh International Conference on Information Technology, 2010

[11] Dr. Ban N. Thanoon "Using Wavelet Transform, DPCM and Adaptive Run length encoding to compress images" 6thInternational Conference on Computer Information Systems and Industrial Management Applications (CISIM'2007).

[12] Kaleka, Jashanbir ,"Performance Analysis of Haar, Symlets and bior wavelet on image Compression using DWT", International Journal of Computerand Distributed Systems, 2012, Vol.1.

[13] Image Compression Using DCT and Wavelet Transformations Prabhakar .Telagarapu, V. Jagan Naveen, A.Lakshmi..Prasanthi, G.Vijaya Santhi GMR Institute of Technology, Rajam -532 127, Srikakulam District, Andhra Pradesh, India. International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 4, No. 3, September, 2011

[14] Minh N. Do and Martin Vetterli, The Finite Ridgelet Transform for Image Representation, IEEE Transactionson Image Processing, January 2003.

[15] D. Vishnuvardhan, Sreenivasan. B, I. Suneetha "Advanced Digital Image Compression Technique Using Curvelet Transform" International Journal of Engineering Research and Applications (IJERA), Vol. 3, Issue 4, Jul-Aug 2013, pp.795-798..

[16] Minh N. Do and Martin Vetterli, The Finite Ridgelet Transform for Image Representation, IEEE Transactionson Image Processing, January 2003.

[17] Rout.S."Orthogonal VS.biorthogonal wavelets for image compresstion", M.SC. Thesis, Virginia Polytechnic Institute and State Unviersity, Blacksburg,Virginia Polytechnic, August 21, 2003.

[18] Mansoor, A.; Mansoor, A.B.; "On Image Compression using Digital Curvelet Transform", 9th International Multitopic Conference, Page (s): 1 - 4, IEEE INMIC 2005.