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A Near Lossless Multispectral Image Compression using 3D-DWT with application to LANDSAT Images

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Abstract— Image compression is a technique which reduces the storage requirements of an actual image with fewer bits. Especially, the high dimensional images need a lot because of the exponential rate of its contained information. As multispectral images are represented in the form of different bands, it is three-dimensional in nature and demands larger memory spaces. There are several lossy and lossless compression methods are available for these types of images and the lossless one is more preferable. But, the problem is that the lossless methods on multispectral images yields better quality images but lack in the compression performance. Hence, there is need for optimal compression method that incorporate both the quality and compression performance. In this paper, we proposed a near lossless compression method for multispectral images. Three-Dimensional Discrete Wavelet Transform is used for decomposition and the Huffman coding followed by thresholding is used for encoding. The results of our proposed method for the multispectral LANDSAT images are discussed and compared with other existing methods in terms of PSNR and SSIM.

Keywords— Near Lossless Compression, Multispectral Image, LANDSAT, 3D-DWT, Huffman Coding.

I. INTRODUCTION

Satellite imaging has its spectrum of utilizations that ranges from earth observation, scientific research, military applications, natural resource management, global environmental monitoring and to the countless of applications. The acquisition of these images is done through remote sensing sensor located from the satellites. It captures the earth with different wavelength and produce large amount of information in the form of different bands. The Multi-Spectral Scanner (MSS) produces the four bands of data, the Thematic Mapper (TM) designed to acquire image with seven bands and the High Resolution Imaging Spectrometer (HIRIS) produces the data with 192 bands [1]. These images are need to archived for learning and further processing with many applications [2]. The archiving and transmission of multispectral image is not the easy task because of the size factor. Hence, it need more amount of memory space and high bandwidth range for storage and transmission respectively due to its high degree of carrying information. Many approaches are proposed for compressing multispectral image.

A vector quantization based methods [3,4], adopts the block based coding techniques in which blocks are operated in spatial domain and a non-linear block prediction is used to feat the spectral correlation. Another lossless method called Mean-normalized vector quantization is also proposed for compressing multispectral images [5]. An extended vector quantization based method that represent the 3-dimensional block using Kronecker Product with smaller vectors is proposed in [6]. In spite of these approaches, transform based methods are very effective with multispectral images [7]. A compression algorithm used Eigenregion-based Eigensubspace transform (ER-EST) [8] for multispectral images which is worked based on the decision rule that derived using principal correlation of an image correlation matrix. Then the eigen regions are classified using the decision rule and the eigen regions are compressed using ER-EST. A quadtree-based KLT transform [9] and wavelet based approaches on 3D domain [10,11] are also proposed for multispectral images. With this literature study, we can conclude that the wavelet based methods paves the way to efficient multispectral image compression especially with the 3D domain. Moreover, these methods may be irreversible and yield better compression performance [12,13]. As quality is the main aspect in the multispectral images, an optimal compression codec is needed that preserve the both compression and quality factors. Hence, in this paper, we proposed a near lossless multispectral image compression method that uses the Three-Dimensional Discrete Wavelet Transform (3D-DWT) and Huffman coding for encoding wavelet frequency coefficients.

The remaining of this paper is organized as follows: Section 2 describes the necessary background knowledge for our proposed method. The methodology and working principle of our proposed method is illustrated in section 3, section 4 contains the evaluated results & discussion and finally we concluded the paper in section 5.

II. BACKGROUND

This section is the discussed forum of background details such as wavelets on 3D space and its decomposition terminologies, thresholding and Huffman coding which is necessary to construct our codec.

A. Discrete Wavelet Transform

There are many transforms are existing, on which some transforms are well suited for image processing such as Fourier Transform [14], Discrete Cosine Transform (DCT) [15], Karhunen–Loeve transformation (KLT) [16] and Discrete Wavelet Transform (DWT) [17]. Among all the transforms DWT is outperformed in image processing field. It is very localized in both frequency and time domain. It uses the scaling and translation operations on image to obtain the necessary coefficients. The multiresolution capability of the DWT improves its efficiency [18] and widely used on image processing field.

The advantages of using DWT:

→ Very easier to implement
→ It analyzes the image at different frequency bands with different resolutions
→ Rich information available for analysis and synthesis
→ Reduced time complexity
→ Decomposition structure with approximation and detail coefficients

B. 3D-DWT Decomposition

The decomposition of an image which in 2D or 3D space is done by means of applying the high-pass and low-pass filtering on each dimension. The approximation coefficients are acquired by applying low-pass filter on every dimension and all other combination on those dimensions gives the detail coefficients. As stated earlier, multispectral images are in three-dimensional space, it is necessary to use 3D DWT on such images. The decomposition structure of the 3D-DWT is show in Figure 1. It shows the single level decomposition structure of the 3D-DWT where eight subbands are acquired from applying filters. Hence, for the 'n' level it produces $7 \times n + 1$ subbands.

III. PROPOSED SCHEME

A. Methodology

The methodology of our proposed method is depicted in figure 2. The input of our method is a LANDSAT image which is obtained from the LANDSAT satellite. It contains the seven bands of images each are captured with different wavelength of a same place.

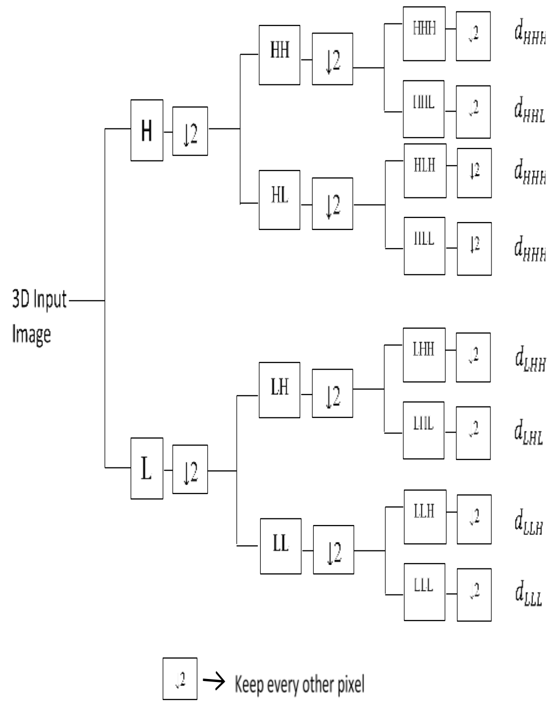

Figure 1. 3D-DWT decomposition structure

The Discrete Wavelet Transform is applied on this LANSAT image and it efficiently exploit both the spatial and spectral correlation. In our method, we use the biorthogonal wavelet on multispectral image by applying the high-pass and low-pass filters accordingly in all three dimensions with the maximum level of decomposition as shown in the Figure 1. After decomposing the original multispectral image, the respective wavelet coefficients are recorded for further processing. The obtained wavelet coefficients are then absorbed to the thresholding stage. The main objective of the thresholding the wavelet coefficient is to make the more zero coefficients. The more number of zero coefficients leads to the significant amount of compression of those images. The manual threshold value is set and coefficient values less than the threshold value are subject to get the zero value. The Huffman encoder is used as encoder which encodes the thresholded coefficients. As Huffman coding proved as a minimum redundancy coding [19], it efficiently encodes the zero coefficients with less amount bits. The outcome of the Huffman encoding addresses as the compressed bit stream of the thresholded wavelet coefficients. Then, the compressed bit stream is subject to transmit for the reconstruction on the decompression stage.

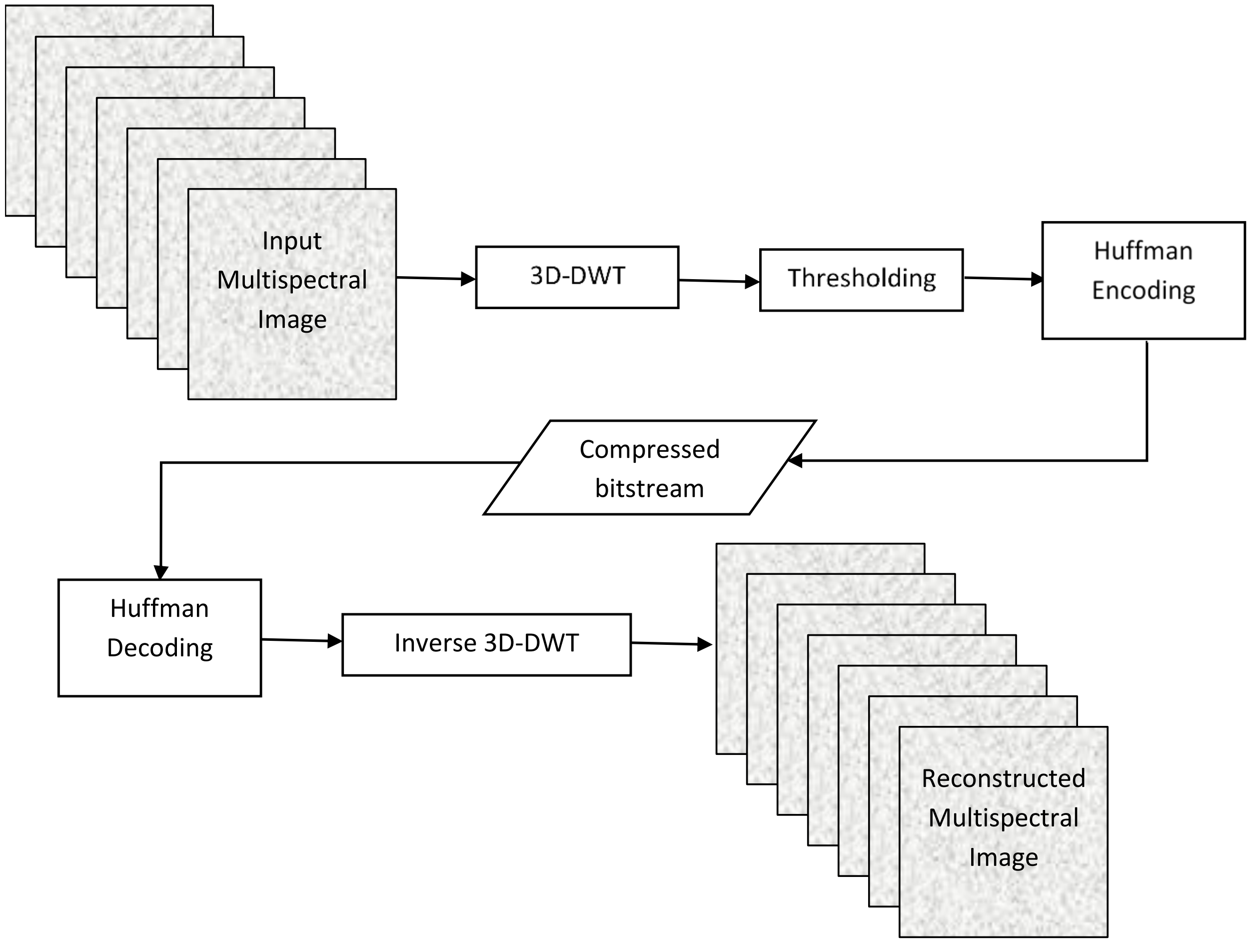

Figure 2. Flow Diagram of our Proposed Method

In the decompression stage the inverse process of phases in compression stage is performed to get the decompressed image. First, with the compressed bit stream the Huffman decoding is performed for decoding. The inverse 3D-DWT is applied on outcome of Huffman decoded file to get the reconstructed image.

The summarization of our proposed method is given below:

Compression

Step1: Input the LANDSAT Multispectral image

Step 2: Decompose the multispectral image using 3D-DWT

Step 3: Threshold the wavelet coefficients

Step 4: Encode the wavelet coefficients using Huffman encoding

Step 5: Compressed Bitstream

Decompression

Step 6: Decode the compressed bit stream using Huffman decoding

Step 7: Apply Inverse 3D-DWT

Step 8: Decompressed Multispectral image

B. Evaluation Metrics

***Compression Ratio (CR)*:** The ratio of original image size and compressed image size is known as the compression ratio(CR).

$$CR = \frac{Original\ bits}{Compressed\ bits} \quad (1)$$

Bits per pixel (BPP): Bits needed for store a single pixel is known as Bits per Pixel (BPP). BPP is

$$BPP = \frac{Size\ of\ compressed\ file}{No.\ of\ pixels} \quad (2)$$

***Peak Signal to Noise Ratio (PSNR)*:** The ratio between the noise and the peak signal is known as Peak Signal to Noise Ratio (PSNR).

$$\text{PSNR} = 10 \ . \ log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (3)$$

where, MAX_I is maximum intensity value in an image and MSE is given as

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[Im(x,y) - Im'(x,y)]^2 \quad (4)$$

where, $Im(x,y)$ is the original image, $Im'(x,y)$ is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the images.

***Structural similarity index (SSIM)*:** SSIM is the HVS based quality Metric. By multiplying the luminance, contrast and the structural term of an image we get the overall index called Structural Similarity (SSIM). The SSIM formula is given below

$$SSIM(x,y) = [l(x,y)]^{\alpha}.\ [c(x,y)]^{\beta}.\ [s(x,y)]^{\gamma} \quad (5)$$

where,

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x{}^2 + \mu_y{}^2 + c_1} \quad (6)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x{}^2 + \sigma_y{}^2 + c_2} \quad (7)$$

$$s(x,y) = \frac{2\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (8)$$

where, μ_x and μ_y are the local means, σ_x and σ_y are the standard deviations and σ_{xy} is cross covariance for images x and y.

IV. Results and Discussion

The first input dataset obtained from courtesy of Space Imaging, LLC and other datasets are obtained from USGS website which publicly known test dataset. Aforementioned, for the decomposition of the images we use the biorthogonal wavelet bior 1.1. We tried with all other wavelet families such as Daubechies, Coiflets and Symlets but biorthogonal wavelet gives better result than the others. The numeric results of our proposed method are given in Table. 1.

The results for five datasets are given in the Table.1. In this table, first column refers the tested dataset, column 2 is given by various threshold values to be tested and the column 3 to column 6 contains the values of Compression Ratio (CR), Bits Per Pixel (BPP), Peak Signal to Noise Ratio (PSNR), SSIM and the Percentage of Zero Coefficients (ZC) on Wavelet coefficients respectively.

Table 1. Numeric results of our proposed method

Dataset	Threshold Value	CR	BPP	PSNR (db)	SSIM	ZC %
Dataset 1	5	3.27	2.44	46.00	0.9987	59.38
	10	4.04	1.98	40.15	0.9951	75.32
	15	4.64	1.72	37.18	0.9902	82.86
	20	5.13	1.56	35.50	0.9850	86.96
	25	5.47	1.46	34.56	0.9802	89.25
Dataset 2	5	4.43	1.80	47.73	0.9987	76.73
	10	5.11	1.56	42.93	0.9963	85.10
	15	5.47	1.46	40.69	0.9937	88.31
	20	5.68	1.41	39.23	0.9905	90.07
	25	5.81	1.38	38.10	0.9867	91.25
Dataset 3	5	4.35	1.83	47.91	0.9990	76.95
	10	4.97	1.60	43.10	0.9969	85.14
	15	5.30	1.50	40.73	0.9946	88.46
	20	5.50	1.45	39.17	0.9918	90.36
	25	5.63	1.41	37.97	0.9884	91.65
Dataset 4	5	4.20	1.90	47.57	0.9987	74.92
	10	4.85	1.64	42.50	0.9959	84.23
	15	5.22	1.53	40.20	0.9930	87.78
	20	5.44	1.47	38.82	0.9900	89.60
	25	5.57	1.43	37.82	0.9867	90.74
Dataset 5	5	4.58	1.74	47.66	0.9987	80.38
	10	5.19	1.54	43.11	0.9966	87.91
	15	5.47	1.46	41.10	0.9945	90.39
	20	5.63	1.42	39.96	0.9924	91.54
	25	5.73	1.39	39.17	0.9901	92.22

These results are taken with various threshold values and zero coefficients are also recorded because of it partially help up to increase the compression performance. The comparison of our proposed method with the traditional Huffman coding method is given in Table 2. We compare our proposed method only with the lossless method but not with lossy method because of the SSIM results. The reason behind this situation is, the SSIM is known as the Human Visual System (HVS) based metric. For the result of Huffman coding (i.e., lossless), it gave lossless reconstruction value as 1. Our proposed method gives 0.9932 which is very close to one and the reconstructed image is almost same as the original image. Hence, our method is compared only with lossless method especially the Huffman coding. While comparing, our method given massive compression performance than the Huffman coding and values of PSNR indicating high quality image and as mentioned above SSIM is very closest to one. BPP is reduced about 4.5 when compared with Huffman coding and probably the compression ratio is increased about 4 times than the Huffman coding.

Table 2. Comparison with Existing Method

Dataset	Huffman Coding				Proposed (Th=15)			
	CR	BPP	MSE (with PSNR= ∞)	SSIM	CR	BPP	PSNR	SSIM
Dataset 1	1.15	6.93	0	1	4.64	1.72	37.18	0.9902
Dataset 2	1.33	5.98	0	1	5.47	1.46	40.68	0.9937
Dataset 3	1.34	5.96	0	1	5.31	1.50	40.73	0.9946
Dataset 4	1.34	5.95	0	1	5.22	1.53	40.20	0.9930
Dataset 5	1.41	5.65	0	1	5.48	1.46	41.09	0.9945
Avg.	**1.31**	**6.09**	0	**1**	**5.22**	**1.53**	**39.98**	**0.9932**

V. CONCLUSION

The near lossless compression for multispectral images was proposed in this paper. The wavelet transform is used with Huffman coding for efficiently coded the image. A 3D-DWT is used for decompose the image and the wavelet coefficients are then encoded with use of Huffman encoding after the thresholding. The results show that our proposed method is very efficiently reduce the space complexity as with better quality. The usage of wavelet and Huffman encoding ensure the compression performance. Hence, our method achieved our target of near lossless property and thus our method boosts up the ease of variety of applications that using satellite imaging.

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