32- Band Hyper-spectral Image Compression using Embedded Zero Tree Wavelet

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Abstract: Hyper-spectral Image is a three dimensional array containing spatial (image) information on x & y axis and spectral information on z axis. It is high resolution imagery. Hyper-spectral image is a dynamic & powerful method to visualize data in terms of spatial & spectral features. It consumes a huge amount of storage. So due to large memory requirements, Hyper-spectral images demand efficient compression. The Hyper-spectral image which we have taken in this paper is the Moffett field image which is taken by Airborne Visible Infra Red Imaging Spectrometer (AVIRIS) satellite. It consumes about 16 GB of space in a day. In this paper we have presented an algorithm which adapts EZW to 3D tree for quantization, Wavelet Transform for decorrelation and Entropy coding is done by Adaptive Arithmetic Coding. The results obtained show the efficient compression and are comparable to JPEG 2000 standard.

Keywords – Hyper-spectral Images, Embedded Zero Tree Wavelet (EZW), Discrete Wavelet Transform (DWT), Arithmetic coding

I. INTRODUCTION

The main strength of Hyper-spectral imagery system is the number of bands. In these type of images we take number of images of same scene at different wavelength. Increasing the band does not mean the accurate information delivery. Though most of the Information is within the spectral axis. So selection of band is important for extracting the critical information. A single spectral cube is shown in figure 1. In the world of internet & multimedia system, we need to deal with huge amount of data storage and data transmission which requires a large bandwidth. Hence an efficient compression is indispensible. Basically compression consists of three steps: Decorrelation, Quantization & Entropy coding. Decorrelation is the step to remove the inter-pixel dependencies in image data which can be achieved by linear prediction, Transform techniques, Multi-resolution techniques etc. Quantization can be done by EZW or its variants. Entropy coding removes the redundancies due to grey level distribution in decorrelated image. It can be achieved by block coding (run-length coding, Huffman coding etc.) or Non-block coding (Arithmetic coding).

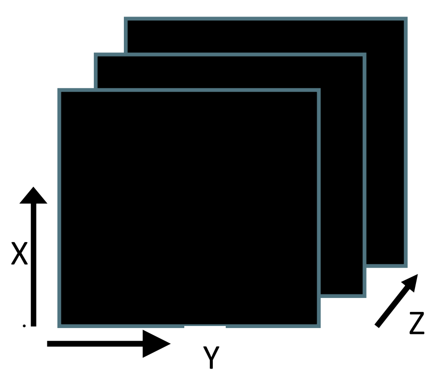

Figure 1: Hyper-spectral Image Cube

The section I comprises an introduction of wavelet transform. Section II gives an idea of image compression with dyadic composition, Zero Tree coding & Arithmetic coding. Section III represents the proposed algorithm. Performance measures & results are presented in section IV & V respectively. Finally section VI concluded the work. In this proposed work we have chosen 3D Wavelet decomposition. For quantization we have used 3D Embedded Zero Tree coding of Wavelet coefficients. Entropy coding is done by Adaptive Arithmetic coding. Wavelet functions are used to analyze the difference subspaces and are represented as

$$\psi_{r,s}(x) = 2^{r/2}\,\psi(2^{r}\,x\text{-}s) \qquad (1)$$

where r = scaling parameter

s = shift parameter

x = continuous time variable

A Wavelet function can be analyzed by using the summation of shifted versions of scaling functions of next higher subspace. Mathematically it is represented as

$$\psi(x) = \sum_n \left[h_\psi(n)\sqrt{2}\,\Phi(2x-n)\right] \qquad (2)$$

where n = shift parameter

Φ = scaling function

h_ψ = coefficient

The main advantage of using Wavelet Transform is that it gives us the space frequency localization. i.e. which frequency is present at which position. It is similar to pin-pointed short time Fourier Transform. Forward Discrete Wavelet Transform (DWT) is represented as

$$W_\Phi(j_0, k) = \frac{1}{\sqrt{M}}\sum_n\left[s(n)\Phi_{j_0,k}(n)\right] \qquad (3)$$

$$W_\psi(j, k) = \frac{1}{\sqrt{M}}\sum_n\left[s(n)\Phi_{j,k}(n)\right] \qquad (4)$$

Where ($j > j_0$)

Here $W_\Phi(j_0, k)$ = scaling function coefficient

$W_\psi(j, k)$ = Wavelet function coefficient

j = scaling parameter

k = shift parameter

s (n) = Discrete-time signal

for n = 0,1…..M-1.

For reconstruction of signal back from the two coefficient is done by Inverse DWT as shown

$$S(n) = \frac{1}{\sqrt{M}}\left[\sum_k W_\Phi(j_0,k)\Phi_{j_0,k}(n)\right] + \frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}\sum_k W_\psi(j,k)\psi_{j,k}(n) \qquad (5)$$

From above equations it can be analyzed that

$$W_\psi(j,k) = \sum_k h_\psi(m-2p)\,W_\phi(j+1,k) \qquad (6)$$

$$W_\square(j,k) = \sum_k h_\phi(m-2p)\,W_\phi(j+1,k) \qquad (7)$$

The above equation shows that DWT uses two filters with impulse responses h_ϕ (scaling analysis filter) & h_ψ (Wavelet analysis filter) with input as original signal [$W_\phi(j+1,k)$]. Figure 2 shows the Block diagram of this filter bank.

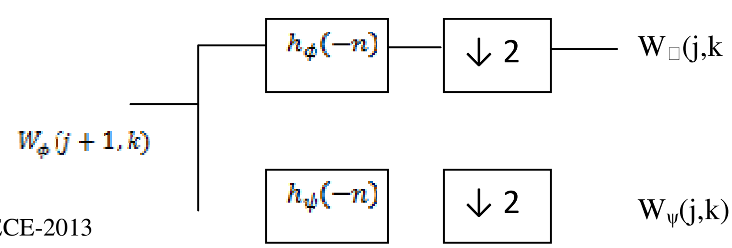

Figure 2 : 1-Level decomposition using filter bank

II. IMAGE COMPRESSION

Compression can be classified as lossless & lossy compression. As the name suggests that in Lossless compression, we do not lose any in information and can reconstruct the original signal. But this type of compression does not provide an effective compression ratio. If we can compromise with some part of information to be loosed then a lossy compression is a better choice. In lossy compression, we lose some information and Perfect reconstruction of signal is not possible. But sometimes reconstructed signal is quite acceptable. The information which we lose in Lossy compression is redundant information. Basically there are three kinds of redundancies in 2D data: Coding Redundancy, Spatial and Temporal Redundancy & Irrelevant information. Thus compression is a step to remove one of these redundancies. There are many standards for image compression. Although Joint Photographic Evaluation Group (JPEG) is a Lossy compression but it uses DCT for decorrelation and run-length coding or Huffman coding for Entropy coding. So we could use JPEG2000 which use Arithmetic coding & DWT. JPEG2000 gives a better quality of compression for photographic images. The part 10 of JPEG2000, also known as JP3D, is targeted for 3D images which are as isotropic as possible. So it does not suit to Hyper-spectral image compression. The paper shows an alternative but less complex approach for these type of compression.

2.1 *Dyadic Wavelet Decomposition*

As Wavelet filters are separable filters so we have applied 1D Wavelet transform in all the dimensions. Although we could apply non-separable filter but it is harder to design such a filter. For a 2D signal [s(n_1, n_2)] we get a bank of filters responses as below:

$$\square(n_1, n_2) = \square(n_1)\,\square(n_2) \qquad (8)$$

$$\psi^H(n_1, n_2) = \psi(n_1)\,\square(n_2) \qquad (9)$$

$$\psi^r(n_1, n_2) = \phi(n_1)\,\psi(n_2) \qquad (10)$$

$$\psi^D(n_1, n_2) = \psi(n_1)\,\psi(n_2) \qquad (11)$$

Where

$\square(n_1, n_2)$ represents the signal Low-pass filtered along the row & along the column. [LL]

$\psi^H(n_1, n_2)$ represents the signal High-pass filtered along the row & Low-pass filtered along the column. [HL]

$\psi^r(n_1, n_2)$ represents the signal Low-pass filtered along the row & High-pass filtered along the column. [LH]

$\psi^D(n_1, n_2)$ represents the signal High-pass filtered along the row & along the column. [HH]

The individual filter responses can be represented individually as in figure 3.

LL	HL
LH	HH

Figure 3: 1-Level Decomposition of 2D Signal

The Low-pass filtered signal is very rich in information. So further decomposition on LL sub-band is done. The 2-level decomposition is shown in figure 4.

<table>
<tr><td>LL_2</td><td>HL_2</td><td rowspan="2">HL_1</td></tr>
<tr><td>LH_2</td><td>HH_2</td></tr>
</table>

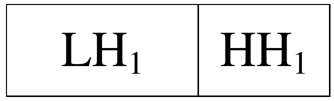

Figure 4: 2-Level Decomposition of 2D Signal

This process of decomposition is known as Dyadic Decomposition. It is to be decided upto which level we should go.

2.2 *Zero Tree Coding of Wavelet Coefficients*

Zero tree provides a multi-resolution representation of Significant Map indicating the position of Significant coefficients. It allows the successful prediction of insignificant coefficients. Successive approximation provides the compact representation of significant coefficients & facilitates embedding algorithm. Larger coefficients are more important than smaller one regardless of their scale. The algorithm runs in recursive manner until the required bit rate is not achieved. Figure 5 shows the flow chart for encoding the Wavelet coefficients in Zero Tree form.

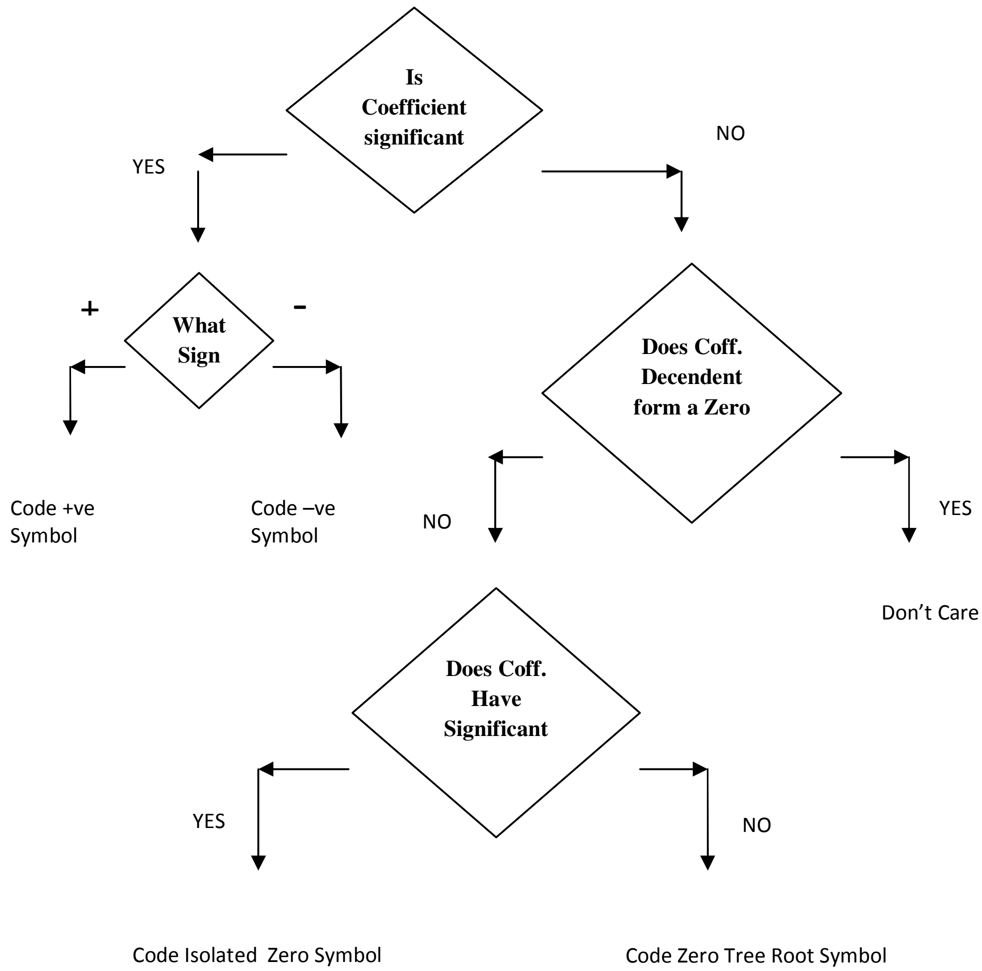

Figure 5: Flow Chart for encoding Wavelet Coefficients

2.3 *Adaptive Arithmetic coding*

Arithmetic Coding is a lossless data compression technique. It encodes the data into the form of a string that represents a fractional value between 0 &1. The bit stream from subordinate pass of Zero Tree coding is hardly to compress. So these are outputted as they are. Arithmetic coding is performed only on the string coded from dominant pass. Probability of each letter in coded string is calculated statically. In case of remote sensing applications where huge amount of data have to be transmitted, higher coding speed is an essential requirement. The proposed scheme gives a higher bit rate saving than any memory less model.

III. COMPRESSION WITH PROPOSED ALGORITHM

The Algorithm for Image compression of Hyper-spectral images is as follows:

1. Download the data file (Moffett Field) from NASA website.
2. Rearrange the data in bit interleaved per pixel (bip) format.
3. Implement a 2D image compression coder using Adaptive Arithmetic coding in MATLAB.
4. Check the efficiency of Adaptive Arithmetic coder.
5. Decide the value for decomposition level & filter type using 2D results.
6. Develop a Hyper-spectral image compression algorithm with Adaptive Arithmetic coding in MATLAB.
7. A file size of 614x512x224x2 is arranged in the size of 512x512 with 32 bands.
8. Design a graph for BPP versus PSNR.

IV. PERFORMANCE MEASURES

The best way to check any signal with the original one is the difference between two signals. The two popular measures are squared error measure & absolute difference measure. If the two signals are x(n) & y(n) then squared error is given by

$$p(x, y) = (x - y)^2 \tag{12}$$

and the absolute error is given by

$$q(x, y) = |x - y| \tag{13}$$

It is difficult to find the difference between the two on the term basis. So we go for Mean Square error (MSE) & it is represented by σ^2.

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(x_n - y_n)^2 \tag{14}$$

If we are interested in size of error relative to the original signal then we can calculate the ratio of the average squared value of original signal to the MSE i.e Signal to Noise ratio (SNR).

$$SNR = \frac{{\sigma_x}^2}{\sigma^2} \tag{15}$$

Where ${\sigma_x}^2$ is the average squared value of original signal. SNR is often measured in decibels (dB).

$$SNR\ (dB) = 10\log_{10}\frac{{\sigma_x}^2}{\sigma^2} \tag{16}$$

Sometimes we are more interested in peak value then we go for Peak Signal to Noise Ratio (PSNR).

$$PSNR\ (dB) = 10\log_{10}\frac{{\sigma_{x_{peak}}}^2}{\sigma^2} \tag{17}$$

V. EXPERIMENTAL RESULTS

To start with an algorithm was developed using 2D wavelet transform for decorrelation, 2D EZW for quantization and run-length or Huffman coding for entropy coding. The decision of filter choice & decomposition level is done by applying 2D compression on Lena256 as shown in figure 6.

Figure 6: Lena 256x256 Image

The results for 2D Lena256 is shown in table 1.

Table 1: Performance of 2D encoder with different decomposition levels (Threshold = 50)

No. of Levels	8	6	5	3
BPP	0.31	0.32	0.32	0.43
PSNR	26.21	26.21	26.21	26.40

From the table it can be observed that beyond decomposition level 5, there is no significant improvement. So we have decided to go for decomposition level of 5. The choice of filter is another main step of compression. The filter has to be chosen which removes aliasing errors, magnitude& phase distortion. Although orthogonal filter are best suited for these problems but they do not provide linear phase which is the prime requirement of image compression. So we go for biorthogonal Wavelet filters. These filters provide linear phase and orthogonal property as well. A better localization can be achieved by them and they are also recommended by JPEG2000 standard too. Table 2 justifies the choice for filter.

Table 2: Performance of various Biorthogonal Filters on Lena512 (Decomposition level = 5, Threshold = 50)

Filter	BPP	PSNR
Bior 1.1	0.22	27.94
Bior 3.5	0.34	31.09
Bior 5.5	0.12	27.53
Bior 4.4	0.17	29.16

From the table it can be observed that bior 4.4 provides a balance between BPP & PSNR.

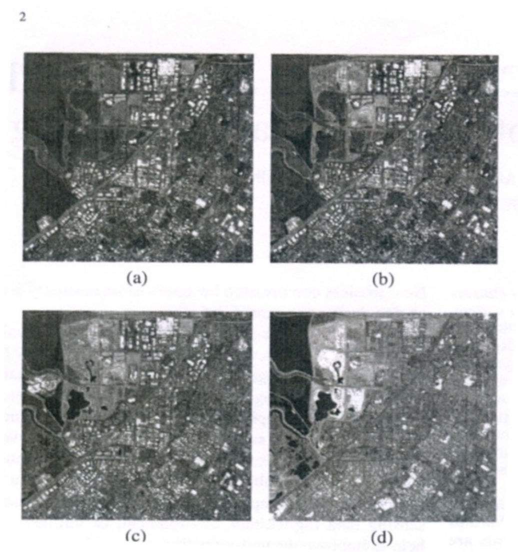

Figure 7 : 2D Slices of Moffett Field image

The objective is to evolve a Hyper-spectral image compression, which is less complex & also provides a better performance. The test data for 3D image compression is the scene of Moffett field, California, at south end of San Francisco Bay imaged by AVIRIS. It is the unique sensor that delivers images in 224 contiguous spectral channels (bands) with wavelengths from 400 to 2500 nanometers. Each band is of 512x614 pixels. The 2D slices of Moffett field are shown in figure 7. The data is in Bit interleaved per pixel (bip) format. The result obtained for spatial dimension of 512x512 with band size of 32 is tabulated in Table 3. The graph drawn from the data shows that as coding size increases performance increases too. So as the Bit per pixel values increases PSNR also increases.

Table 3 : AVIRIS Moffett Field 512x512x32 (Decomposition level = 5, Filter = bior 4.4)

Threshold	100000	40000	20000	10000	4000	2000
Bits per pixel	0.00485	0.00677	0.01068	0.04401	0.28000	0.72733
PSNR	42.77	44.03	44.49	46.92	51.48	53.85

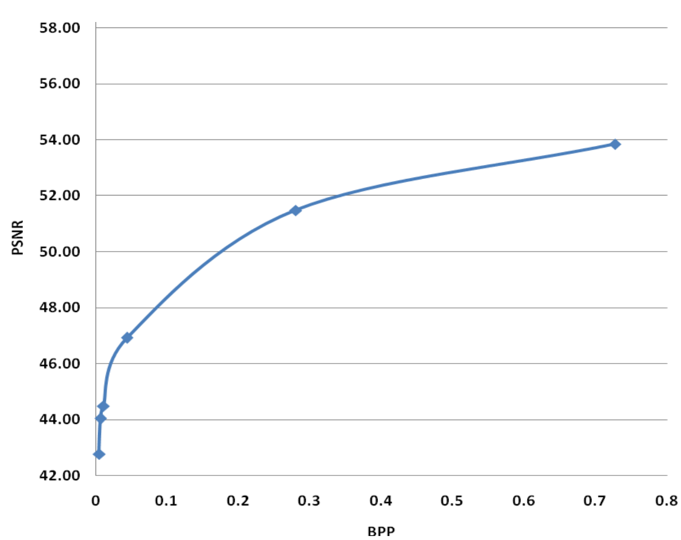

Figure 7: Performance for 3D coding size of 32 band

VI. CONCLUSION

In this paper we have presented an algorithm which is less complex & provides a fully embedded bit stream. This is most suitable for the on-board processing of hyper-spectral images on space systems. The gain results achievable in the coding time by using the presented adaptive arithmetic coder is significant also compared to the adaptive counterpart. Many choices are made from 2D results & on applying it on 3D, it is concluded that performance improves with the coding.

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