8- BAND HYPER-SPECTRAL IMAGE COMPRESSION USING EMBEDDED ZERO TREE WAVELET

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ABSTRACT

Hyperspectral imaging is a powerful technique and has been widely used in a large number of applications, such as detection and identification of the surface and atmospheric constituents present, analysis of soil type, monitoring agriculture and forest status, environmental studies, and military surveillance. 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. In this paper we have presented an algorithm which adapts EZWfor 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

Hyperspectral images are generated by collecting hundreds of narrow and contiguously spaced spectral bands of data such that a complete reflectance spectrum can be obtained for the region being viewed by the instrument. All substances, including living things, have their own spectrum characteristics or diagnostic absorption features.

However, at the time we gain high resolution spectrum information, we generate massively large image data sets. Access and transport of these data sets will stress existing processing, storage and transmission capabilities. As an example, the Airborne Visible Infra Red Imaging Spectrometer (AVIRIS), a typical hyperspectral imaging system, has 224 sensors. In order to provide sufficient resolution to detect most absorption features, each sensor has a wavelength sensitive range of approximately 10 nanometers. All sensors together yield contiguous spectral bands covering the entire range between 380 nm and 2500 nm. If each band is 614 × 512 scans (pixels), with one byte per pixel, the whole data set will be over 70 Mbytes. Actually, AVIRIS instrument can yield about 16 Gigabytes of data per day. Therefore, efficient compression should be applied to these data sets before storage and transmission.Obviously, the low compression ratio is not enough to cope with serious data management issues such as hyperspectral image transmission. However, if we are willing to lose some information, we can gain significantly higher compression ratio than that of lossless compression. This is so-called lossy compression (lossy coding).

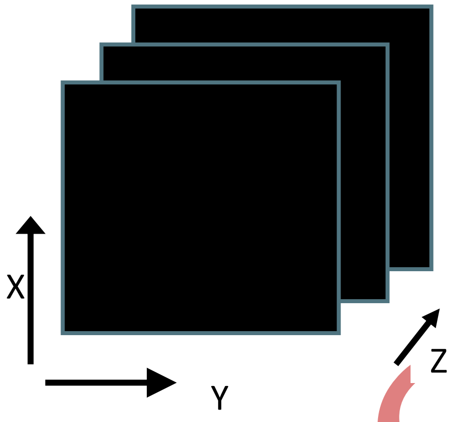

Figure 1: Hyper-Spectral Image Cube

JPEG 2000 is the latest international standard for still image compression. The JPEG 2000 encoding is basically a transform coding scheme. To allow for progressive decoding and error resilience, the system is based on the concept of Embedded Block Coding with Optimal Truncation (EBCOT). Entropy coding is achieved by an arithmetic coder that compresses binary symbols relatively to an adaptive probability model associated with different coding contexts. The optimal truncation point for each code block is chosen using the Post-Compression Rate-Distortion optimization (PCRD-opt) algorithm which is complex and computationally demanding. Moreover Part 10 of JPEG 2000, also known as JP3D, is targeted for three-dimensional images which are, however, as isotropic as possible. This requirement does not suit hyperspectral images which are anisotropic, and also they exhibit a higher correlation in spectral dimension than the spatial dimensions. Hence wavelets which show a good adaptability to a wide range of data, while being of reasonable complexity is chosen for decorrelation. A hyperspectral image compression algorithm is proposed with 3D anisotropic wavelet decomposition using separable filters with optimum decomposition level for decorrelation., an algorithm based on the adaption of Embedded Zero Tree Wavelet (EZW) to 3D tree for quantization and a novel adaptive arithmetic coder where the probability distribution was statically calculated using histogram based zerothorder Markov model for the outputs of the dominant passes of EZW for each successive threshold. 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.Quantization can be done by EZW or its variants. Entropy coding removes the redundancies due togrey level distribution in decorrelated image.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

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

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

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

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

$$W_\Phi(j_0,k) = \frac{1}{\sqrt{M}}\sum_n \left[s(n)\Phi_{j_{0,k}}(n)\right] \quad (3)$$

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

Where ($j > j_0$)

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

W_ψ(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

$$S(n) = \frac{1}{\sqrt{M}}\left[\sum_k W_\Phi(j_0,k)\Phi_{j_{0,k}}(n)\right] + \frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}\sum_k W_\psi(j,k)\psi_{j,k}(n) \quad (5)$$

From above equations it can be analyzed that

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

$$\mathbf{W_\phi(j,k)} = \sum_k \boldsymbol{h_\phi(m-2p) W_\phi (j+1,k)} \qquad \textbf{(7)}$$

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.

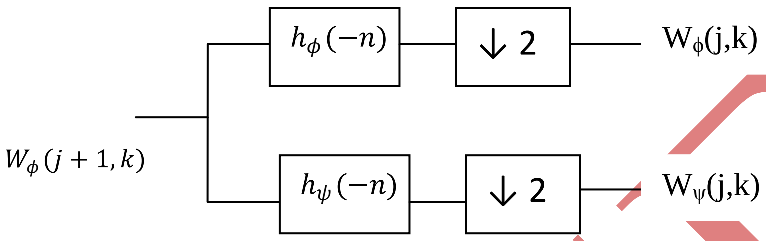

FIGURE 2: 1-Level Decomposition Using Filter Bank

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. 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:

$$\boldsymbol{\phi(n_1,n_2) = \phi(n_1)\, \phi(n_2)} \qquad \textbf{(8)}$$

$$\boldsymbol{\psi^H(n_1,n_2) = \psi(n_1)\phi(n_2)} \qquad \textbf{(9)}$$

$$\boldsymbol{\psi^r(n_1,n_2) = \phi(n_1)\, \psi(n_2)} \qquad \textbf{(10)}$$

$$\boldsymbol{\psi^D(n_1,n_2) = \psi(n_1)\, \psi(n_2)} \qquad \textbf{(11)}$$

Where

$\phi(n_1, n_2)$ 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>
<tr><td colspan="2">LH_1</td><td>HH_1</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.

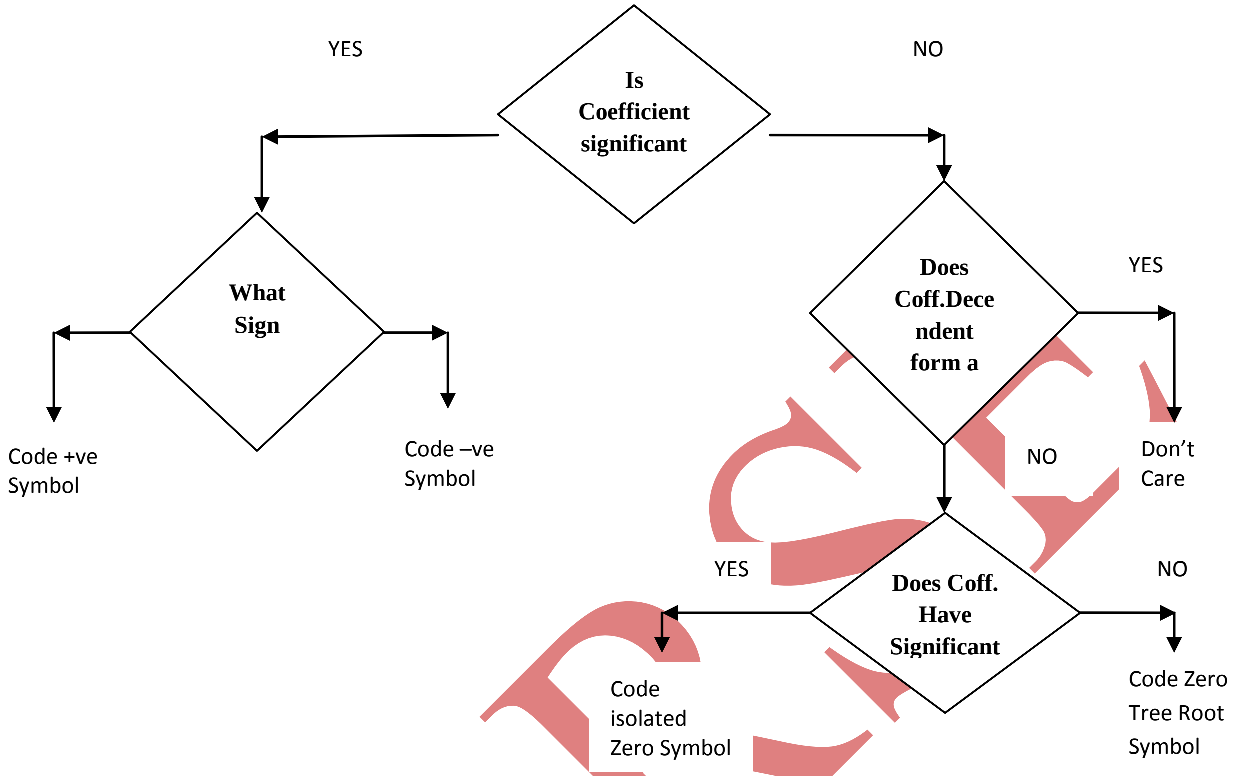

Figure 5: Flow Chart for Encoding Wavelet coefficients

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.

2.4 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 8 bands.
8. Design a graph for BPP versus PSNR.

III 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

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

And the absolute error is given by

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

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.

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

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).

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

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

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

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

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

IV EXPERIMENTAL RESULTS

An algorithm was developed using 2D wavelet transform for decorrelation, 2D EZW for quantization and 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. 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.

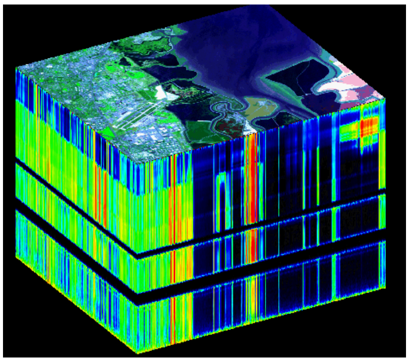

Figure 7: Moffett Field Image Cube

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. The data is in Bit interleaved per pixel (bip) format. The result obtained for spatial dimension of 512x512 with band size of 8 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 512x512x8 (Decomposition Level = 5, Filter = Bior 4.4)

Threshold	3000	2000	1000	500
BPP	0.12256	0.20273	0.56400	1.34052
PSNR	52.03	53.16	55.72	58.33

V 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.

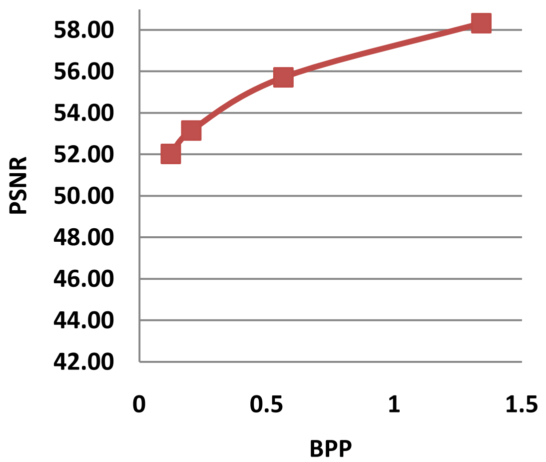

Figure 8: Performance for 3d Coding Size of 8 Bands

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