Hyper Spectral Image Compression Using Fractal Compression with Arithmetic and Huffman Coding

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Abstract: *hyper spectral (HS) image compression approaches achieved significant advances from diverse types of coding standards/approaches. HS image compression requires an unconventional coding technique because of its unique, multiple-dimensional structure. Compression of hyper spectral images is undertaken to reduce the on-board memory requirement, communication channel capacity and the download time. Compression algorithms can be either lossless or lossy. In hyper spectral image compression, wavelets have shown a good adaptability to a wide range of data. Some wavelet-based compression methods have been successfully used for hyper spectral image data. Fractal Image Compression is an approach for better image compression. The main objective of this method is to provide simple and better compression results, which is based on proposed Quad tree Decomposition and Discrete Wavelet Transform method for a hyper spectral image. Fractal image compression can be obtained by dividing the RGB image into un overlapped blocks depending on a quantization value and the well-known techniques of Quad tree decomposition. The experiments are conducted with HSI compression based on DWT, Fractal. The results of our work are found to be good in terms of Compression Ratio (CR) and Peak Signal-to-Noise Ratio (PSNR).*

Key words: HSI, DWT, CR, PSNR

1. Introduction

Many military and civil applications involve the detection of an object or activity such as a military vehicle or vehicle tracks. Satellites must transmit a great amount of information to control on earth for its later processing. If the satellite carries out a preprocessing step in order to extract only the relevant information the communication process will be highly optimized. Hyper Spectral Images (HSIs) are used in several applications such as soil analysis, forest monitoring, river flow analysis, environmental studies and other geographical analysis. HSI sensors are advanced digital color cameras with spectral resolution at a specific illumination wavelength. These sensors measure the radiation reflected by each pixel in a large no of visible or invisible frequency (or wavelength) bands. HSIs are considered as 3D data in compression methods known as third-order tensor, composing of two spatial dimensions and a spectral dimension.

The benefits of compressing hyper spectral images are: a) the reduction of transmission channel bandwidth; b) the reduction of the buffering and storage requirement; c) the reduction of data transmission time at a given rate. Because of the limited available resources and processing capabilities in space borne and airborne platforms, on board encoding complexity is an important issue in hyper spectral compressions.

Compression considers the tradeoff among these factors: processing capabilities, end-user applications and data quality (lossless or lossy), and constraints (memory and hardware) of space borne and airborne instruments. The greatest challenges are addressed on onboard image compression. First at all, due to the large amount of data collected and the limited transmission capacity, there is no doubt that the data have to be stored on the satellite or aircraft. However, this onboard storage is limited. The data have to be processed on the fly as they are acquired. The image compression algorithm has to be executed on the fly, that is, they have to start being compressed as images are acquired. Moreover, the compression has to be a low-complexity algorithm and have constant throughput because of the limited processing capability [1].

Other important properties of hyper spectral image compression include random access, progressive decoding, resolution scalability, standard format, and flexibility. The property of random access is to encode and decode selected portions of interest in a hyper spectral image. Since a small portion is encoded instead of the entire image, it reaches a high compression ratio without sacrificing any information in the image and can be reconstructed at high quality. The feature of progressive decoding is that the reconstruction fidelity is improved as more information is regained.

2. HSI Compression Methods:

A typical compression algorithm utilizes statistical structure in the image data set. In hyper spectral images, two types of correlation are possible. One is spatial correlation that exists between adjacent pixels in the same band, and the other is spectral correlation that exists between pixels in adjacent bands. In this paper spectral correlation has been considered.

Lossless Compression Techniques for HSI:

Adaptive Edge Based Prediction this is done by concentrating on increased affinity between the pixels present in the edge of the images to put forth a new high performance compression algorithm. The algorithm uses three different types of predictors for different modes of prediction. Intra band prediction is done using an improved median predictor (IMP) that can detect the diagonal edge [2].

Double-Random Projection Method this method uses randomized dimensionality reduction techniques for efficiently capturing global correlation structures and residual encoding. This new method extended from the randomized matrix decomposition methods for achieving rapid loss less compression and reconstruction of hyper spectral imaging (HSI) data, ensures effective lossless compression of HSI data.

A Transform Based Lossless Compression This method was inspired by Shapiro's Embedded Zero tree Wavelet (EZW) algorithm. The method that is proposed for compression employs a hybrid transform which is a combination of an integer Karhunen-Loève transform (KLT) and integer discrete wavelet transform (DWT). [2]

Context Prediction Based Lossless Compression algorithm performs sequentially linear prediction, followed by 3D context prediction followed by arithmetic coding and exhibits low complexity and a compression ratio, which is better than many states of art algorithms.

Lossy Compression Techniques for HSI:

Lossy Compression for Exomars Algorithm was specifically designed to be able to perform on- board compression, achieving high coding efficiency and meeting other very important requirements for onboard compression at the same time, namely low complexity, error resilience, and hardware friendliness. The algorithm applies a scheme consisting of a prediction plus a Golomb power-of- two entropy coder. It partitions the data into units, which are portions of the hyper spectral cube of size N×N pixels with all bands and can be compressed independently.

Lossless & Lossy Compression Techniques for HSI:

Distributed source coding (DSC) compression algorithm compression algorithm is for both lossy and lossless compressions. The complexity of the algorithm is found to be very low. It uses regression model to improve the compression performance of distributed lossless compression algorithm, and optimal scalar quantization for distributed lossy compression [5]

3. Proposed algorithm:

Fractal method using arithmetic coding:

In our methodology, Image Compression technique uses quad tree decomposition and dwt method. The Fractal Image Compression is suitable techniques for hyper spectral image compression. [6]

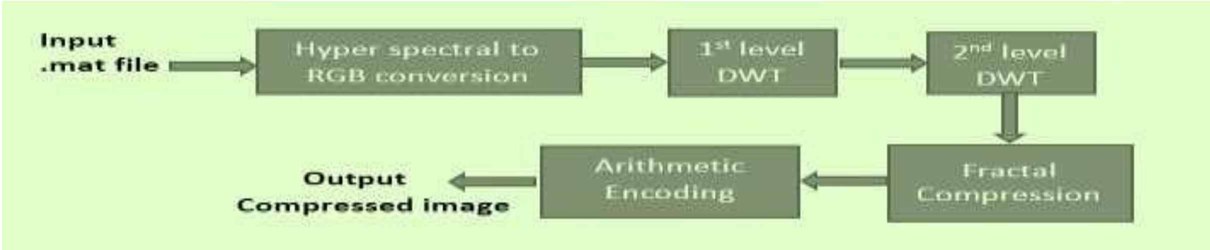

Fig: Block Diagram of Compression

Fig: Block Diagram of Decompression

HSI to RGB Conversion

Hyper spectral imaging combines spatial and spectral data in such a way that each pixel of an image of a scene or object represents a continuous radiance or reflectance spectrum. Terminology in spectral imaging is not standardized, but can be indicative. In turn, multispectral imaging differs from conventional trichromatic or RGB color imaging, where spectral sampling is reduced to just three components, from the long-, medium-, and short- wavelength regions of the visible spectrum.

DWT Compression:

This section illustrates the proposed compression technique with pruning proposal based on discrete wavelet transform (DWT). The proposed technique first decomposes an image into coefficients called sub-bands and then the resulting coefficients are compared with a threshold. Coefficients below the threshold are set to zero. Finally, the coefficients above the threshold value are encoded with a loss less compression technique.

The compression features of a given wavelet basis are primarily linked to the relative scarceness of the wavelet domain representation for the signal. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using the following elements: a small number of approximation coefficients (at a suitably chosen level) and some of the detail coefficients.

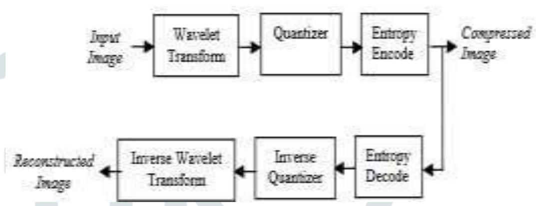

Fig: DWT approach block diagram

Fractal method

In fractal compression firstly Image is divided into a number of square blocks called range, later the image is divided into bigger square blocks, called domain blocks, which are usually four times larger than the range block. After that, the domain blocks are searched for the best match for every range block. For every range block the number of the appropriate domain and relevant information needed to retrieve that range are stored. The fractal affine transformation is constructed by searching all of the domain block to find the most similar one and the parameters representing the fractal affine transformation will form the fractal compression code.[6]

The decoder performs a number of iterative operations in order to reconstruct the original image. This process is very time consuming and during encoding time it takes a lot of time. It is very difficult to calculate domain block for every range block and it is very time consuming so we calculate the mean value of every block. It is too much difficult to remember the huge data base for searching the best one domain block for respective range block with affine transformation formulas and we go for calculate mean value of every block with respective to their x and y coordinates.

To calculate the mean value of every block for quad tree decomposition given formula is used.

Mean (I) = S I(X, Y)/n

Variance = S (I(X, Y)-M)*2/n

Arithmetic coding

Arithmetic coding is a data compression technique that encodes data (the data string) by creating a code string which represents a fractional value on the number line between 0 and 1. The coding algorithm is symbol wise recursive; i.e., it operates upon and encodes (decodes) one data symbol per iteration or recursion. On each recursion, the algorithm successively partitions an interval of the number line between 0 and 1, and retains one of the partitions as the new interval. Thus, the algorithm successively deals with smaller intervals, and the code string, viewed as a magnitude, lies in each of the nested intervals. The data string is recovered by using magnitude comparisons on the code string to recreate how the encoder must have successively partitioned and retained each nested subinterval. Arithmetic coding differs considerably from the more familiar compression coding techniques, such as prefix (Huffman) codes.

4. Parameters for Evaluation

A. Compression ratio (CR)

Compression ratio is used to measure the compression efficiency. Compression ratio is the ratio of original image and compressed image. As compression ratio increases the image quality increases. CR=Size of original image/Size of compressed image.

B. Mean Squared Error (MSE):

The difference between original image data and compressed image data is called mean square error (MSE). MSE is inversely proportional to PSNR, as MSE decreases the PSNR increases. PSNR indicate quality of image. Image compression is lossless when MSE is zero. It’s better to have less MSE.

C. Peak Signal to noise Ratio (PSNR)

PSNR is the ratio between maximum signals powers to noise appear in signal. PSNR is related to quality of image. For good quality of image the PSNR of image should be high. PSNR is depends upon the mean square error (MSE) of image. When the difference between the original image and compressed is less the PSNR is high so eventually the quality of image is also high.

5. Results:

The Data set 1 is taken from the .mat file library of size 1021x1338x33 which is then divided into 33 bands and then fractal is applied using arithmetic coding and Huffman Coding to get the original, compressed and Decompressed Image.

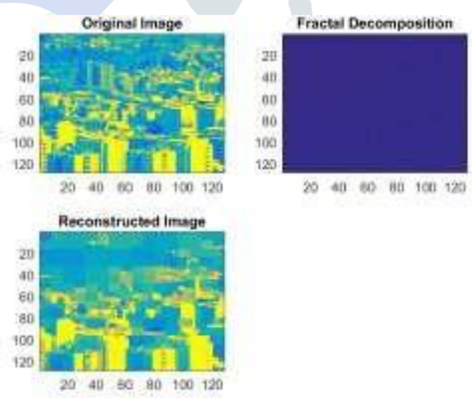

Fig: Fractal Result of Data set 1

The Data set 2 is taken from the .mat file library of size 1018x1339x33 which is then divided into 33 bands and then fractal is applied using arithmetic coding and Huffman Coding to get the original, compressed and Decompressed Image.

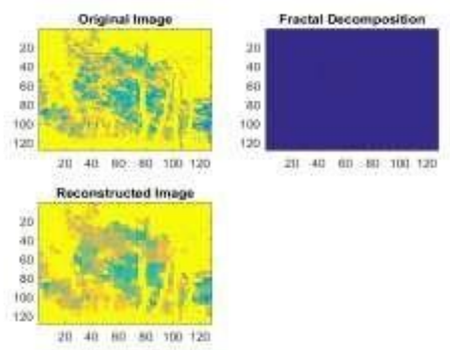

Fig: Fractal Result of Data Set 2

Band number	Compression ratio	PSNR(dB)
1	32.27	59.96
2	30.86	61.46
5	29.49	63.91
6	29.55	64.57
10	31.17	61.44
12	32.27	55.46
14	33.16	49.53
19	33.97	47.96
20	33.79	48.13
25	33.59	49.56
26	33.33	49.97
29	32.95	51.07
30	33.08	50.54
31	33.11	49.73
33	33.62	49.39

Table: Fractal arithmetic coding result of Data Set 1

PARAMETER	DWT	FRACTAL (Huffman Coding)	FRACTAL (Arithmetic Coding)
Avg Compression ratio	84.51	17.25	34.11
Avg PSNR(dB)	48.19	55.39	55.39

Table: Numerical Results of Data Set 1

PARAMETER	DWT	FRACTAL (Huffman Coding)	FRACTAL (Arithmetic Coding)
Avg Compression ratio	84.53	22.41	34.55
Avg PSNR(dB)	48.52	52.49	52.49

Table: Numerical Results of Data Set 2

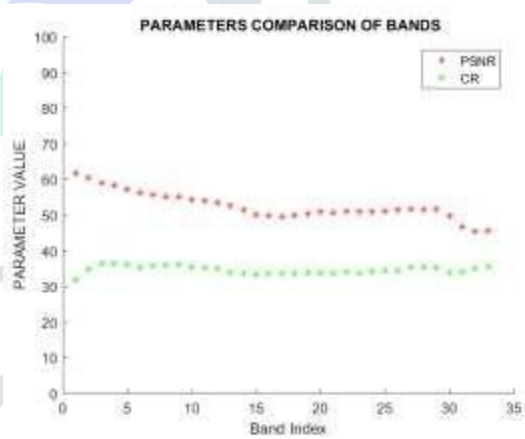

Fig: PSNR & CR Graph of Fractal Data set 2

The above graph represents the parameters i.e. PSNR & CR. All the 33 Bands of PSNR & CR represents in the graph, the X-axis as shows the range from 0-35 because the no. of bands are only 33 and on Y-axis it represents frequency 0-100 because Max PSNR is 61dB and Min PSNR is 48dB and the Max CR is 48 and Min CR is 31.

6. Conclusion

In fractal image compression the block size play a very important role. The quality of image and time is depended on the block size according to their dimensions and quantization value. We show compression and decompression results for various different images. The future scope methodology is that we will change the dimensions of the image and we will also calculate the threshold value and calculate the time of compression and decompression. Our work was found to be good in terms of CR and PSNR value. The future work involves the development and simplification of the fractal calculations to decrease the memory consumption, computational load and processing time for the HSI compression.

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