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Wavelet based Compression of Hyper Spectral Image cube using Tensor Decomposition

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***Abstract:* - As the dimensionality of remotely sensed Hyper spectral images are increasing, compression is required to transmit and archive Hyper spectral data. In this paper, an adept method for Hyper spectral image compression is presented to effectively reduce the volume of Hyper spectral data. The objective of proposed method is to apply classical compression method where low frequency information is reserved and high frequency information is discarded, based on Discrete Wavelet Transform. The core idea of our proposed method is to apply tucker decomposition on the wavelet coefficient, exploit both the spectral and the spectral information in the images. Moreover, it also evaluates the compression ratios for biorthogonal wavelet family The obtained result shows better performance on Bior1.1 and Bior1.3 wavelets.**

***Index Terms*—Hyper spectral Images, Compression, wavelet transform, tucker decomposition, Biorthogonal wavelet.**

I. INTRODUCTION

Hyper spectral image cube is a set of hundreds of spectral images, which corresponds to different wavelength of sensed images. Such images cover great detail of valuable information about the region under investigation.

Hyper spectral image is sequence of image generated by collecting contiguously spaced spectral bands of data spanning a vast region of electromagnetic spectrum ranging from 0.001 µm to 14 .0 µm. The first operational application of remotely sensed earth data in 1980 was in the field of mineral exploration. It also contributes to geological investigations such as monitoring health of crops, mapping minerals, oil resources in the earth [1]. Also helps in identification & imaging capability for chemical warfare agents in military & surveillance and historical manuscript research.

Hyper spectral image provides data containing both spectral and spatial information. Huge volume space is required to store this data. Several factors make the constraints particularly stringent and the challenge exciting. First is the size of the data: as a third dimension is added, the amount of data increases dramatically making the compression necessary at different steps of the processing chain. Also different properties are required at different stage of processing chain with variable tradeoff. Second, the differences in spatial and spectral relation between values make the more traditional 3D compression algorithm obsolete. And finally, the high expectation from the scientists using Hyper spectral data requires the assurance that the compression will not degrade the data quality. However the large size of Hyper spectral image data often limits the possible use of processing techniques and also requires large volumetric area. In order to solve this problem the author aimed to considerably reduce the dataset size without losing neither spectral nor spatial information . As compression relies on the statistical structure in the data, there are basically two types of correlations available. One is spatial correlation in adjacent pixels of the same band; other is the spectral correlation in the pixels between adjacent bands[2]. The spatial correlation can be easily exploited using general compression techniques; however, the solution how to efficiently explore the redundancy between adjacent bands of higher resolution is not yet well established [3]. One of the challenges in processing Hyper spectral imagery is its huge data volume may result in high computational cost of data processing, long delay of data transmission and communication. This difficulty can be addressed by developing techniques reducing data size, referred as data reduction / compression.

Data compression has received increasing interest in Hyper spectral data analysis because of the vast amount of data volumes to be needed processed and significantly redundancy resulting from high interband spectral correlation, spectral information is usually more essential and crucial than spatial information. Therefore, effective compression is required to deal with these problems. Several compression methods have been proposed which can be classified into two main types: Lossy and Lossless. Lossless method compress the image by encoding all the information form original file ,after reconstruction the image will be exactly identical to original[3],[4] and the maximum achievable order is around 3:1 , whereas in lossy there will be a possibility of data/information loss. But it should be under the limit of tolerance.

The data compression can significantly reduce Hyper spectral data volumes to more manageable sizes for storage and communication. Many compression techniques from their long history are providing excellent dimensionality reduction for Hyper spectral image in recent years. The approach can be grouped into Predictive coding, Vector quantization and Transform based coding. Predictive coding requires complicated to implement the sophisticated predictors that produce the optimal difference between predicted and actual value. On the other hand, transform coding is most efficient and simpler because of useful properties of energy compaction and decorrelated data in the transformed image. Overall, transform coding is good candidate for on-board Hyper spectral data. Vector quantization group the images into set of vectors or blocks, then choose a subset of input vector as a training set. Then a codebook is generated from the training set. Finally, the output is compared with input vector. Some researchers consider combining the vector quantization with transform based coding such as EZW, SPIHT, SPECK etc.

The most common approach, dimension reduction was often applied by means of Principal Components Analysis (PCA)[5] or Independent Component Analysis (ICA) which helps to examine which component would like to retain[6]. However, they did not consider the spatial correlation when focusing on the spectral decorrelation. Later, Pearlman proposed an improved approach known as Set Partitioning in Hierarchical Trees (SPIHT) [7], a 3D wavelet based techniques with advanced implementation of the EZW algorithm through partitioning the hierarchical tree structure. Another low complexity image encoder which requires low dynamic memory, Set Partitioned Embedded bloCK (SPECK) for Hyper spectral image compression have been proposed to exploit a joint consideration of the spatial and spectral correlations [8]. It has been shown in that 3D-SPECK is better than 3D-SPIHT to achieve an efficient compression. In [9], a PCA-based method in conjunction with JPEG2000 for compressing HSIs was introduced. The results reveal that the performance of the method is superior to that of the spectral DWT, and the best PCA performance occurs when a reduced number of PCs are retained and encoded. Another compression algorithm based on JPEG2000 for HSIs was proposed in [10] which were well suited for dimensionality reduction and anomaly removal. The algorithm can be applied for lossy and near-lossless compression applications in one single tool. It was also shown that the proposed scheme has a negligible effect on the results of selected applications (e.g., hard classification, spectral unmixing, and anomaly detection). Another algorithm, that employs a Kalman filter in the prediction stage was proposed, it was later on observed that it employs only the previous band of prediction [11].

In this paper, we investigate the compression ratio and peak signal to noise ratio of a Hyper spectral image based on discrete wavelet transform and tucker decomposition . First, we apply 2DWT to each spectral band of image, thereby proceeding with the first stage of compression using biorthogonal wavelet family. Second, we apply TD to the four wavelet sub-images of the HSIs in order to attain more compression. Third, we apply inverse DWT to reconstruct the image. Finally, using the observations for different wavelet filters as well as compression ratio and peak signal to noise ratio to corresponding wavelet, we generated a performance analysis chart to estimate the optimal compression ratio and PSNR for biorthogonal wavelet family. Our experiment indicates that bior1.1 and bior1.3 achieves better compression ratio as well as the PSNR in comparison to other wavelets of boirspline.

II. PROPOSED APPROACH

a. Wavelet Transform

Wavelet based method are widely used for compression of Remote sensing images and data. Wavelet transform with characteristics like multiresolution analysis, compact support, linearity are powerful tools for image processing [12].Discrete wavelet has the ability to display the images at different resolution and also achieves higher compression ratio [13]. In DWT, image is represented by sum of wavelet functions known as wavelets. Image is first divided into blocks i.e the images are divided into 1/4 sizes sub-images and the wavelet analysis is done by filter banks. The Figure 1 illustrates 2-level DWT decomposition wherein, X[n] is the input signal, d (n) is the frequency component and a (n) is the low frequency component. There are two types of filters: High Pass and Low Pass filters. In high pass filter high frequency components are preserved whereas in low pass high frequency is lost and low frequency are obtained [14]. It effectively decomposed the input into two parts (N × N images), a detailed coefficient (high frequency) and approximation coefficient (low frequency) they are further separated as (LL) Low-frequency, (HL, LH and HH) High-frequency components. Then all the coefficients are discarded except the LL coefficient that is transformed into the second level. These coefficients are then passed through a constant scaling factor to achieve the desired compression ratio. When two-dimensional DWT is applied to each band of Hyper spectral images , if each image band has I_1 rows and I_2 columns, then after applying 2DWT, we obtain four sub-bands (A, V, H, D) each having $I_1/2$ rows and $I_2/2$ columns. The A is considered to have highest energy among all the coefficients [15].

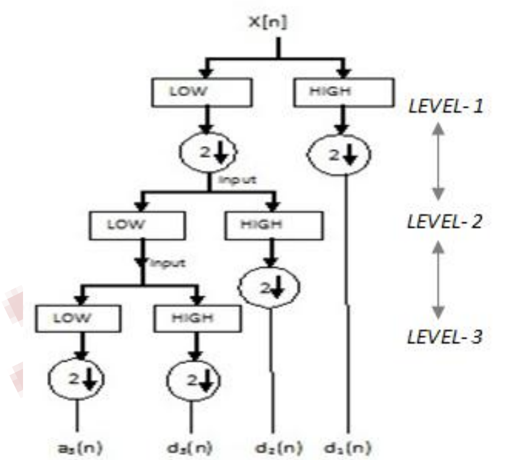

Fig. 1: Decomposition tree of DWT

The Figure 2 points up the decomposition of Hyper spectral image in proposed system. The DWT is used in many image processing applications such as noise reduction, edge detection and compression. As it uses only the dyadic scales that are power of 2, i.e. 2, 4,8,12 and so on. Each scale refers to a level that is level=$\log_2$(scale) .The DWT can decompose any high dimensional image by implementing one dimensional DWT on each dimension separately.

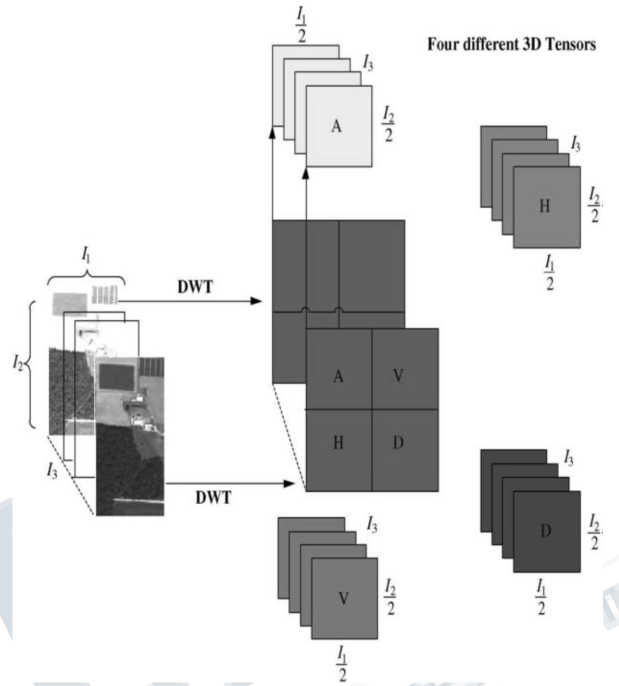

Fig. 2: Decomposition scheme on the proposed method for HSIs.

b. Tensor Decomposition

A tensor is multidimensional or N-way array. Two particular type of tensor decomposition can be considered to be higher-order extensions of the matrix singular value decomposition: CANDECOMP/PARAFAC (CP) decomposes a tensor as a sum of rank-one tensor and Tucker decomposition is a higher order of principal component analysis, named after Ledyard R. Tucker. The author/// applied tucker decomposition in proposed algorithm for to decompose the tensor into a set of matrices and one small core tensor.

For each tensor, the size of the core tensor $\underline{G}$, i.e. (J1, J2, J3), was selected manually. The approximate tensor has the lowest frequency components containing most of the wavelet coefficient energy, so the values of (J1A, J2A, J3A) were set higher than those of other tensors. The values of (J1D, J2D, J3D) for the diagonal tensor, which contains the diagonal information, were also set higher than the (J1H, J2H, J3H) and (J1V, J2V, J3V) values of horizontal and vertical tensors.CR (Compression Ratio) also calculated in this module [14].

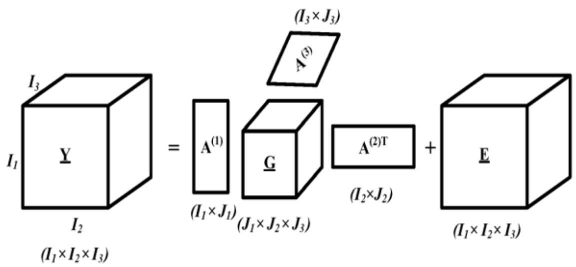

Fig.3. Third-order Tucker decomposition

The third-order TD tensor (as in Figure 3) is described as a decomposition of a given third order tensor $\mathbf{Y} \in \mathbf{R}^{I_1 \times I_2 \times I_3}$ into an unknown core tensor G $\in R^{J_1 \times J_2 \times J_3}$ multiplied by a set of three unknown components matrices where, $A^{(n)} = [a_1^{(n)}, a_2^{(n)}, \ldots\ldots a_n^{(n)}] \in R^{I_n \times J_n}$ where (n=1,2,3) represents the common factor[15].

$$Y = \sum_{j_1=1}^{J_{1=1}} \sum_{j_2=1}^{J_2} \sum_{j_3=1}^{J_3} g\, j_1 j_2 j_3\ a_{j1}^{(1)} .\ a_{j2}^{(2)} .\, a_{j3}^{(3)} + \underline{E}$$

$$= \underline{G} \times_1 A^{(1)} \times_2 A^{(2)} \times_3 A^{(3)} + \underline{E}$$

$$= \underline{G} \times \{A\} + E = \underline{Y} + \underline{E}$$

Here tensor $\hat{\mathbf{Y}}$ is an estimation of tensor $\mathbf{Y}$, and it depends on the $(J_1 J_2 J_3)$ values, which are the dimensions of the core tensor $\mathbf{G}$, and tensor $\mathbf{E}$ denotes the estimation error[16].

III. PROPOSED COMPRESSION ALGORITHM

The core idea behind the proposed system is to apply Hyper spectral image compression algorithm based on discrete wavelet transform.The next stage is to apply tucker decomposition to wavelet sub-images to efficiently compact the energy of sub-images .As it has the ability to reduce the spatial and spectral correlation. After applying wavelet transform to each band in the initial stage followed by tucker decomposition in next stage , the experimental result is calculated every for Biorthogonal wavelet family. Finally, inverse DWT is applied to reconstruct the image.

The steps followed by the proposed hybrid method based on discrete wavelet transform and tucker decomposition (DWT + TD) as per Figure 4 are:

1. Input the Hyper spectral image $\underline{X}$ (size $I_1 \times I_2 \times I_3$).
2. Apply 2-DWT to effectively separate HSIs into different sub-images.
3. Use the above method on each spectral band to obtain sub-images(A,V,H and D).
4. Apply TD algorithm efficiently compact the energy of sub images. Each tensor has the size of $(I_1/2) \times (I_2/2) \times I_3$).
5. Compute the TD on each tensor and quantize the significant element to be encoded.
6. Decode the elements.
7. Calculate the inverse 2DWT to reconstruct images.
8. Final reconstructed output image is obtained.
9. Repeat Step 1 to 8 for every biorspline wavelets (15 wavelets) families.
10. Design a graph for Band versus PSNR.

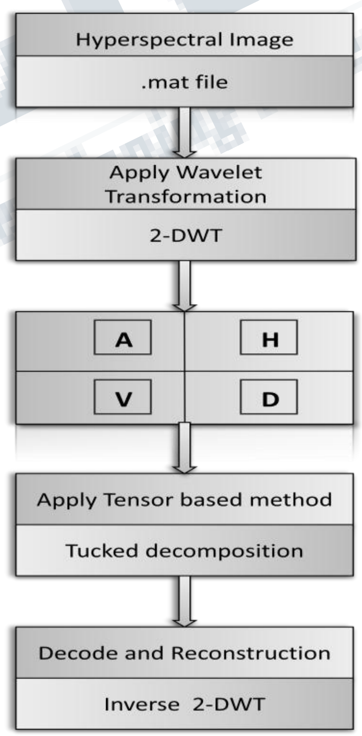

Fig.4. Proposed System Architecture

We applied the proposed algorithm on Scene

4(Figure 5) image set, a Hyper spectral image obtained during summer 2002 and 2003 from the region of Portugal. These scenes are the interpretation of reflectance spectra from natural scenes. The raw image is acquired by a Hyper spectral camera, immediately after acquisition the reflected spectrum in the scene is recorded with a telespectro radiometer(Spectra Colorimeter ,PR-650).The estimated reflectance spectra at each pixel in the scene is converted into MATLAB scene-reflectance file(1018×1337×33).

These .mat files are used in the proposed system as dataset. In this paper the author also examines the effect of PSNR on different biorthogonal wavelets. A biorthogonal wavelet is wavelet where associated wavelet transform is invertible but not necessary orthogonal. Biorthogonal wavelet allows more degree of freedom than orthogonal wavelet. The set of Biorthogonal filter is used in this experiment. Biorthogonal family has perfect symmetry a linear phase of wavelet and Nr and Nd orders are the associated filter length.

Fig.5. Hyper spectral dataset SCENE 4(Cyflower)

IV. EXPERIMENTAL RESULT

A. Experimental setup

The proposed approach is implemented using MATLAB 7.10.0.499(R2010a) with system configuration of 2GB RAM Intel Processor. The experiment was done using the data from[17] which is a Hyper spectral ground based image. Here, we have taken the HSI image for compression and the CR of reconstructed image have been observed for various wavelet(approximate 10 wavelet considered) to analyze the best CR and highest PSNR.

To measure the perceptual quality of image, performance evaluation parameters are to be considered. Two popular performance evaluation parameters are Peak Signal to Noise Ratio (PSNR) and Compression Ratio (CR).

PSNR is the most popular tool for the measurement of the compressed image and video. PSNR is a measure of peak error between the compressed image and the original image[18]. PSNR value should be higher for higher quality of image reconstruction. It is most easily defined via the mean squared error (MSE). The PSNR in decibel is evaluated as follows:

$$PSNR = 10log_{10}\frac{I^2}{MSE}$$

Where , I is allowable image pixel intensity level.MSE is mean squared error, yet another performance evaluation p'arameter of Image compression algorithm.It compares the original data with reconstructed data and then results the level of distortion. Typical values of PSNR in lossy image and video compression are between 30 and 50 dB.[ref SAIM].

Compression Ratio is the measure of reduction of detail coefficient of data.It is the term used to quantify the reduction in data-representation size produced by a data compression algorithm[19].Compression Ratio in this approach can be considered as ratio between the total number of bits in the original input data,and the number of bits must be transmitted and shown as:

$$CR = \frac{Uncompressed\ Data}{Compressed\ Data}$$

The set of Biorthogonal filter(biorNr.Nd) is used in this experiment. There are 15 wavelets in this family out of which 10 are considered , which gives the most optimal CR for the Hyper spectral image dataset. The orthogonal filters are best suited for prime requirement of image compression[20]. The choice of filter is another step of compression in used by author in this paper.

B. Experimental Results

The experiment was carried out using a Hyper spectral dataset [SCENE-4(Cyflower)[17],which was obtained from the rural area of Portugal during daylight in summers of 2002 and 2003. The scenes are illuminated by direct sunlight in clear sky. The dataset is a Hyper spectral reflectance image (Matlab file) with size 1018 by 1337 pixels and 33 bands.We tested the hybrid algorithm on dataset of 33 bands and calculated the psnr values gained by proposed algorithm at different biorthogonal wavelet families.The biorthogonal wavelet family contain 15 wavelets out of which ten wavelets are considered by the author in this paper, which yields better PSNR. The wavelet families included in this paper are bioi1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.3, bior3.5 and bior3.7.

First ,we apply the proposed algorithm(DWT+TD) to these images. Next, we obtained the PSNR values achieved for each band by the proposed algorithm. The same method is repeated for each wavelet and quality metrics graph for PSNR is achieved. The Figure 6 and Figure 7 show the sample graph of high and low compression ratios for HSI and PSNR versus Band Index for bior wavelet.

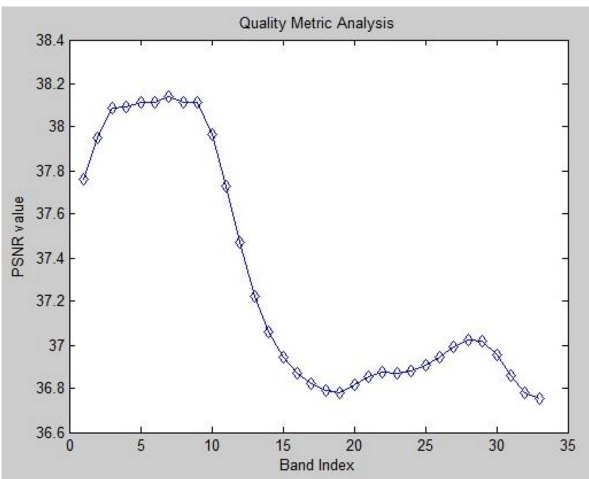

Fig.6 : Band Index Versus PSNR values for High CR.

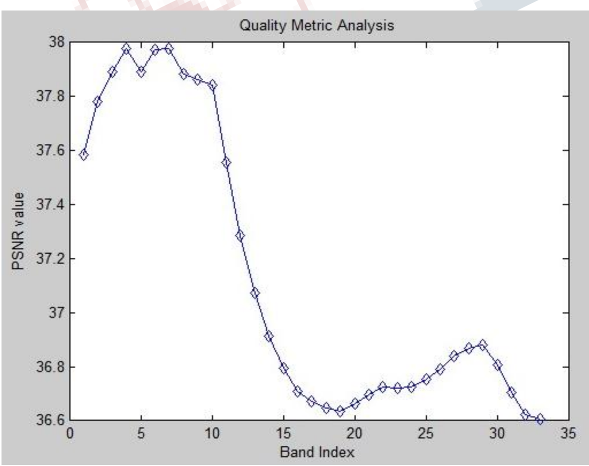

Fig.7 : Band Index Versus PSNR values for Low CR

The Figure 8 illustrate a graph which shows that, for higher compression ratio the PSNR is low and for lower compression ratio the PSNR is higher.

TABLE I
COMPRESSION RESULT

PSNR(in dB) and Compression Ratio of DWT+TD algorithm using various wavelets

Wavelet	CR	PSNR
Bior2.4	3.5	38.37
Bior2.6	3.5	38.35
Bior1.1	3.7	38.14
Bior1.5	3.5	38.14
Bior1.3	3.6	38.10
Bior3.3	3.6	38.09
Bior2.8	3.4	38.08
Bior3.5	3.5	38.04
Bior2.2	3.6	37.99
Bior3.7	3.4	37.98

The TABLE I shows the result of values obtained for peak signal to noise ratio over different wavelets and corresponding compression ratios.

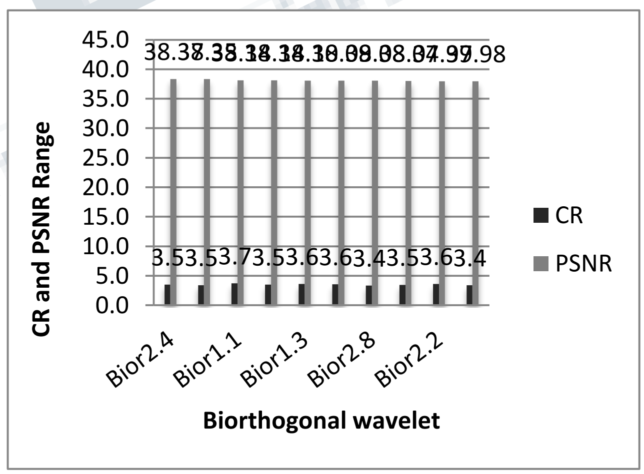

Fig.8: Graph showing ranges of compression ratio and PSNR for various wavlets.

V. CONCLUSION

In this paper , we have presented an algorithm which is used for HSI compression using DWT and TD. We apply a compression technique of reducing the size of 3D tensors computed from four wavelet sub-images of the spectral bands of HSI. It is also applied on various Bior wavelet families to obtain competitive compression ratios.The overall best performance is attained for Bior 1.1 and Bior1.3. Here, the wavelet based algorithm gets higher PSNR values for low compression ratio.

In future works, we aim to lower the computational load of the proposed method in order to speed up the compression process. So as to make it suitable for On-board processing of Hyper spectral images.

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