ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

Hyperspectral Band Clustering on EBCOT Pre Encoding Technique

Dr.T.Arumuga Maria Devi[1], I.Rajeswari[2]

Assistant Professor, Dept. of CITE, MS University, Tirunelveli, Tamilnadu, India[1]

M.phil Scholar, Dept. of CITE, MS University, Tirunelveli, Tamilnadu, India[2]

ABSTARCT: The image compression based on principal component analysis (PCA) provides good compression efficiency for hyperspectral images. However, PCA might fail to capture all the discriminant information of hyperspectral images, since features that are important for classification tasks may not be high in signal energy. To deal with this problem, in this a hybrid compression method namely, Embedded Block Coding with Optimized Truncation (EBCOT) is proposed for hyperspectral images with pre-encoding discriminant information. A feature extraction method is first applied to the original images, producing a set of feature vectors that are used to generate feature images and then residual images by subtracting the feature-reconstructed images from the original ones. Both feature images and residual images are compressed and transmitted. Experiments results indicate that the proposed method provides better compression efficiency with improved classification accuracy than conventional compression methods.

KEYWORDS: PCA, EBCOT, Pre-encoding, Compression, JPEG2000

I. INTRODUCTION

Hyperspectral imaging combines the power of digital imaging and spectroscopy. Hyperspectral imaging collects and processes information across the electromagnetic spectrum [1]. The goal of hyperspectral imaging is to obtain the spectrum for each pixel in the image, with the purpose of detecting objects. For each pixel in an image, a hyperspectral camera acquires the light intensity (radiance) for a large number (typically a few tens to several hundred) of contiguous spectral bands [2]. Every pixel in the image thus contains a continuous spectrum (in radiance or reflectance) and can be used to characterize the objects in the scene with great precision and detail. The recent advancement in sensor technology provides remotely sensed data which has a large number of spectral bands [4]. So, Efficient compression techniques are needed for hyperspectral images.

There are many studies are presented in both lossless and lossy compression techniques latter it can achieve higher compression ratios than the literature. To remove spectral redundancy most compression technique most lossless techniques resort to prediction, whereas most lossy techniques resort to transform-based approaches. Transform-based methods are followed by two-dimensional transforms such as the discrete wavelet transform or the discrete cosine transform. In that Wavelet transform-based methods have drawn great interest, too, and a number of two dimensional wavelet based techniques have been extended to three dimensional applications, including set partitioning in hierarchical trees, set partitioning embedded block and tarp coding. The region-based coding schemes have been studied that often yielding improved SNR performance [7], [8]. Also most lossy compression methods have been developed to minimize mean squared errors between the original and the reconstructed pixels. However, discriminant information required to distinguish between the various classes is also vital for classification purposes applications. As an example, JPEG2000 coders coupled with spectral PCA produce good performance in terms of SNR [11], [12], but their classification accuracy may not be satisfactory [14] since they may not effectively preserve the discriminant features for classification, mostly because these features may not be large in terms of energy.

In this paper, a hybrid compression method called, Embedded Block Coding with Optimized Truncation (EBCOT) is proposed for hyperspectral images with pre-encoding discriminant information. First a feature extraction method is applied to the original images that producing a set of feature vectors that are used to generate feature images and then

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

residual images by subtracting the feature-reconstructed images from the original ones. Then feature images and residual images are compressed and transmitted. Experiments results indicate that the proposed method provides better compression efficiency with improved classification accuracy than conventional compression methods. The simulation results show that the proposed method has high SNR value, efficiency, compression ratio and low MSE.

II. RELATED WORKS

This section discusses various techniques involved in hyperspectral image compression method. Ian Blanes and Joan Serra-Sagrista [1] have proposed clustered versions of Karhunen–Loeve Transform for remote sensing image coding. It provides a good solution and as they require much less computational resources than the KLT. The coding performance is maintained while it is applied over multiple levels and these are compatible with the use of subsampling in the covariance calculation, a technique that virtually removes transform training costs. For classification based approaches it needs to apply a transform further and it provides low signal to noise ratio.

Pier Luigi Dragotti et al. [2] have proposed two techniques. First a three-dimensional transform is taken and a simple 3-D SPIHT is used. The spectral vectors of pixels are vector quantized after taking a spatial wavelet transform and a gain-driven SPIHT is used. It needs contextual classifier further is to avoid the noise and provide reliable results. Barbara Penna et al. [3] have proposed transform design and rate allocation stage for lossy compression of hyperspectral data. A set of 3-D transforms are selected which is obtained by combining in various ways wavelets packets, wavelet, Karhunen–Loeve transform and discrete cosine transform and then evaluate the coding efficiency of these combinations. Then take low-complexity version of the KLT, in which complexity and performance can be balanced in a scalable way. But it provides some erroneous signal to compressed data. Marco Cagnazzo et al. [4] have proposed region-based approach for multispectral image coding. In a rate-distortion sense it can be effective thus providing an image description that is both insightful and efficient. But it needs some improvement in segmentation side. Lena Chang et al. [5] have proposed a group and region based parallel compression approach for hyperspectral imagery. It contains two algorithms, which are clustering signal subspace projection (CSSP) and the maximum correlation band clustering (MCBC). The CSSP first divides the image into proper regions by transforming the high dimensional image data into one dimensional projection length. The MCBC partitions the spectral bands into several groups according to their associated band correlation for each image region. The execution time will be higher.

Xaoli Tang et al. [6] have proposed 2D SPECK to 3D sources such as hyperspectral images Three-Dimensional Set Partitioned Embedded bloCK (3DSPECK). For an image sequence, three dimensional discrete wavelet transform (3D-DWT) is applied to obtain a wavelet coefficient prism. It provides channel error during transmission. Qian Du et al. [7] have proposed Principal component analysis (PCA) to provide spectral decorrelation as well as spectral dimensionality reduction and that is deployed in JPEG2000. It can be evaluated in terms of rate-distortion performance as well as in terms of information preservation in an anomaly-detection task. It provides good performance in terms of rate distortion but it has less classification accuracy [13-17].

III. EMBEDDED BLOCK CODING WITH OPTIMIZED TRUNCATION

It is an entropy coding algorithm for two dimensional wavelet transformed images that generate a bit-stream having resolution and quality. This scheme partitioning each sub-band in a small group of samples namely code book. It separates layered bit-stream for each code-block is generated. This algorithm is based on bit-plane coding; context adaptive binary arithmetic coding and to code new information four coding passes are employed for a single sample with current bit-plane. They are zero coding, run-length coding, sign coding and magnitude refinement. A combination of run length coding and zero coding passes encodes sample c becomes significant in the current bit-plane. A sample c is said to be significant in the current bit-plane if and only if $|c|\geq 2^p$. The sign coding pass uses five different context models to encoding the sign information of sample only if the sample becomes significant in the current bit-plane. Three different context models are used by magnitude refinement pass to encoding the value of sample only if it is already significant in the current bit-plane p. [13-17].

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

This scheme may employ EBCOT to code the wavelet coefficients on a slice-by-slice basis. However, in this compression method, the input samples to the entropy coding algorithm are 3D-IWT wavelet coefficients rather than 2D-IWT wavelet coefficients. The 3D-IWT wavelet coefficient on a slice-by-slice basis makes EBCOT less efficient since the correlation between coefficients is not exploited in three dimensions.

Consequently, a Modified Embedded Block Coding with Optimized Truncation (MEBCOT) algorithm is needed to overcome this above problem, which can be solved by partitioning each 3-D sub-band into small 3-D groups of samples, which is called as code-cubes and coding each code-cube independently with a modified EBCOT. In this proposed scheme, the code-cubes are comprised of a×a×a samples and describe a specific region of the 3-D image at a specific decomposition level. This scheme employs a pyramid approach to define the size of code-cubes across the different decomposition levels. The code-cube of size a×a×a samples and position {x, y, z} at decomposition level r is related to a code-cube of size samples a/2×a/2×a/2 and position {x, y, z} at decomposition level r+1, where r=1 is the first decomposition level. It can be seen that by employing a pyramid approach to define the size of code-cubes, it is possible to access any region of the 3-D image at any resolution, which is essential for VOI coding. In this work, we limit the code-cube dimension, to be a power of 2, this method codes each code-cube independently using a modified EBCOT with 3-D contexts that exploit inter-slice correlations. Coding wavelet coefficients by extending 2-D context modeling to 3-D has been extensively used to improve coding efficiency. Here, this method proposes a 3-D context model, based on the four coding passes previously discussed, that incorporates information from the immediate horizontal, vertical, diagonal and temporal neighbors of sample located in slices. During the ZC pass, we code whether or not sample becomes significant in the current bit-plane p. The significance of sample is highly dependent upon the value of its immediate horizontal, vertical and diagonal neighbors. Here, in order to exploit interslice correlations, we also employ the information about the significance of the immediate temporal neighbors to code the significance of sample.

IV. HYBRID COMPRESSION METHOD

A. Feature Extraction and Feature Images

Linear feature extraction can be viewed as a linear transform. The feature extraction method produces a set of feature vectors $\{\beta_i\}$, and an extracted feature is computed as follows:

$$y_i = \beta_i^T X \qquad (4.1)$$

Where X represents an observation in the N-dimensional space. In most cases, the set of feature vectors $\{\beta_i\}$ can be considered orthonormal. A number of feature extraction methods have been proposed for pattern classification in the past, including canonical analysis and decision boundary feature extraction (DBFE). In this letter, this compression method selects DBFE because it can utilize both the mean and covariance differences; however, any other feature extraction method can be used for the proposed compression method. Most feature extraction methods, including canonical analysis and DBFE, use covariance matrices, which should be invertible. Due to high correlations between adjacent bands, the covariance matrix of hyperspectral images may not be invertible even with a large number of training samples. To deal with this problem, this compression method uses the band combination procedure and the band expansion method. Figure. 1(a) and (b) shows a block diagram of the proposed compression method. This method assumes that the original images contained N spectral bands and K pixels in each band. We let $J_1, J_2, \ldots, J_N$ be the N spectral bands, where J_i was a $K \times 1$ column vector. For notational convenience, these vectors were presented in a $K \times N$ matrix, i.e., $J = [J_1, J_2, \ldots, J_N]$. First, we apply feature extraction to the original images based on a set of given classes. This process will produce a set of feature vectors. It is assumed that the set of feature vectors forms an orthonormal basis. In this case, the following feature vector matrix can be viewed as a unitary transform:

$$B = [\beta_1, \beta_2, \ldots, \beta_N] \qquad (4.2)$$

where β_i is an $N \times 1$ column vector. Let X be a pixel vector of the original image, which corresponds to each column vector of $J^{T.}$ Then, we can represent X as a linear combination of $\{\beta_i\}$, i.e.,

$$X = \sum_{j=1}^{N} y_j \beta_j \qquad (4.3)$$

where $y_j = \beta_j^T$ represents an extracted feature found by a feature extraction method. In most cases, it is possible to retain most of the discriminant information with a small number of extracted features. Using these extracted features, a subset of extracted feature images is produced as follows:

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

$$F_i = J\beta_i = [J_1, J_2, \ldots, J_N]\beta_i$$
$$= \beta_{i,1}J_1 + \beta_{i,2}J_2 + \cdot \quad \cdot \quad \cdot + \beta_{i,N}J_N \ (i = 1, \ldots, S) \quad (4.4)$$

where $\beta_{i,j}$ represents the jth component of β_i, F_i is the ith extracted feature image, and S is the number of extracted features. From now on, we will refer to these extracted-feature images as feature images.

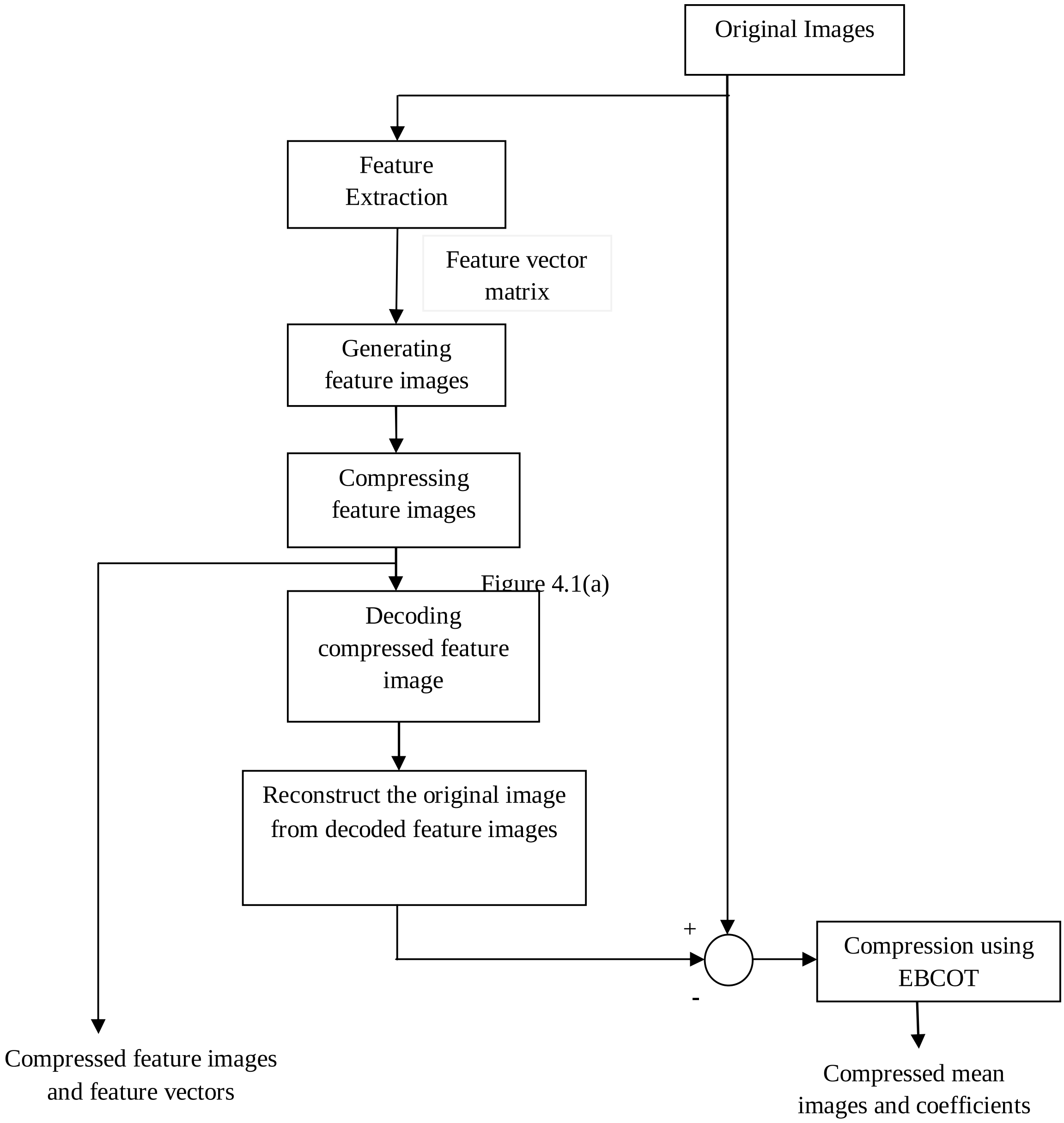

Figure 4.1(a)

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

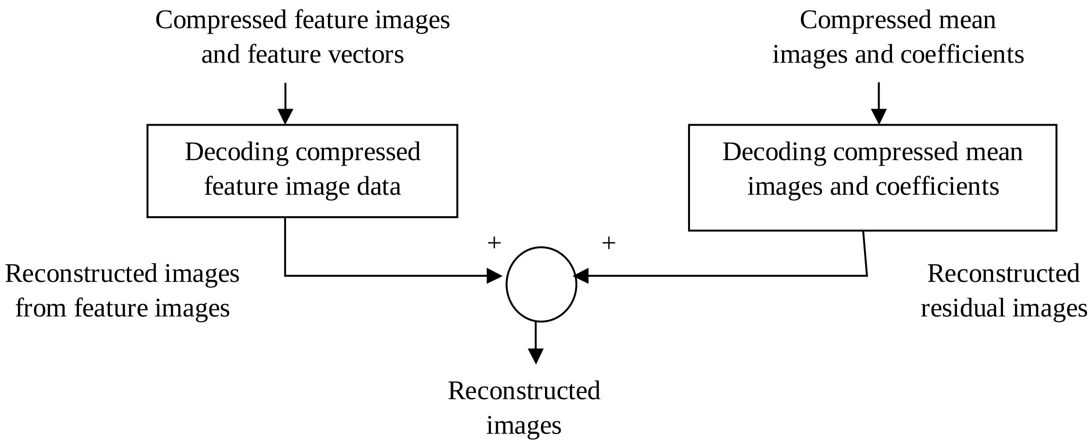

Figure 4.1(b)

These S feature images are encoded, and the corresponding feature vectors are quantized. Any 2-D or 3-D image compression method can be used to compress the feature images, but it uses embedded block coding with optimized truncation approach due to its superior compression performance. From the encoded feature images and feature vectors, the original images can be reconstructed. In other words, a pixel vector of the original image can be reconstructed as follows:

$$\hat{Z} \approx \sum_{j=1}^{N} \hat{y}_j \hat{\beta}_j \qquad (4.5)$$

where $\hat{y}_j$ represents the pixel value of the *jth* feature image. Thus, we reconstructed the original images from the decoded feature images, which are called "feature-reconstructed" images and denoted by $\hat{J}$feature. By subtracting the feature reconstructed images from the original images, we generated residual images, i.e.,

$$J_i^{res} = J_i - \hat{J}_i \text{feature i } (i = 1, \ldots, N). \qquad (4.6)$$

Figure 4.1 Block Diagram of proposed compression method. (a) Encoding, (b) Decoding.

EBCOT was applied to these residual images, and a subset of eigenimages was compressed with 1-D + 2-D JPEG2000 in this letter. In other words, each band of a residual image is represented as follows:

$$J_i^{res} \approx \sum_{j=1}^{n} c_{j,i}\, \varphi_j + \hat{\mu} \; (i = 1, \ldots, N) \qquad (4.7)$$

where $\{\varphi_i\}$ is an eigenvector ($K \times 1$) of the covariance matrix of the residual images as calculated, $\hat{\mu}$ represents a reconstructed mean image ($K \times 1$), and $c_{j,i} = \varphi_i^T (J_j^{res} - \hat{\mu})$. $\{\varphi_i\}$ represents the eigenimages of the residual images, and the coefficients $\{c_{j,i}\}$ are quantized. From the compressed eigenimages and quantized coefficients, we can produce reconstructed images, i.e.,

$$\hat{J}_i^{res} \approx \sum_{j=1}^{n} \hat{c}_{j,i}\, \hat{\varphi}_j + \hat{\mu} \; (i = 1, \ldots, N) \qquad (4.8)$$

where $\hat{J}_i^{res}$ represents the reconstructed *i*th residual image, $\hat{c}_{j,i}$ is a quantized coefficient, and $\hat{\varphi}_i$ is the reconstructed *i*th eigenimage. Finally, the hyperspectral images are reconstructed by adding the reconstructed feature images to the reconstructed residual images [see Figure. 1(b)]. In the following experiments, the mean image $\hat{\mu}$ was compressed at 3.46 bits per pixel, and 32 bits were used for quantizing each coefficient since the memory requirements for coefficient quantization were negligible compared to the memory requirements for image data.

V. PERFORMANCE ANALYSIS

The Indian Pine Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data set was used for performance analysis [10]. This data set contains 250 spectral bands and the spatial size of the bands is 2168 × 616 pixels. From the data set, a subregion of 256 × 256 pixels has been widely used by remote-sensing researchers. [11-12].

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

The simulation is done in MATLAB simulator and the parameters such PSNR, MSE, Compression ratio and efficiency are calculated.

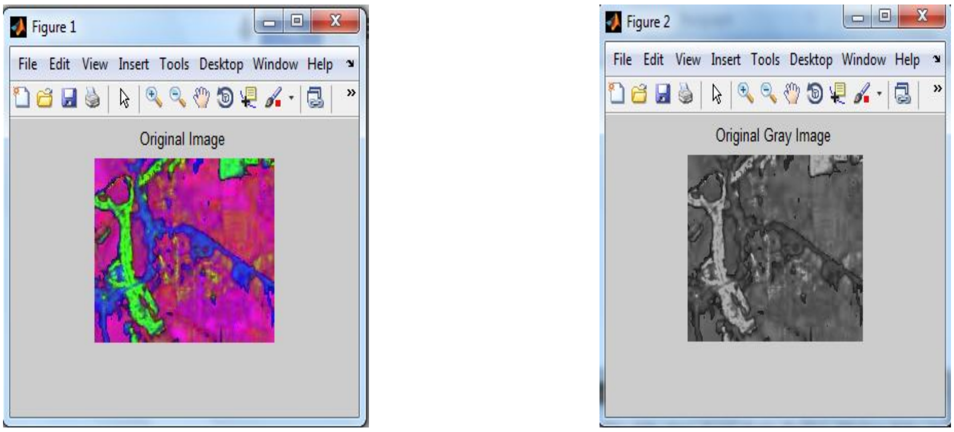

Figure 4.2 (a) Hyperspectral Original Image **(b) Original Hyperspectral Gray Scale Image**

The figure 2(a) shows the original input hyperspectral image. The Hyperspectral band images having set of sub bands. This sub bands classified depends upon the RGB bands. The figure 2 (b) shows that the original gray scale image. The hyperspectral image is converted into gray scale image to calculate the feature values of images.

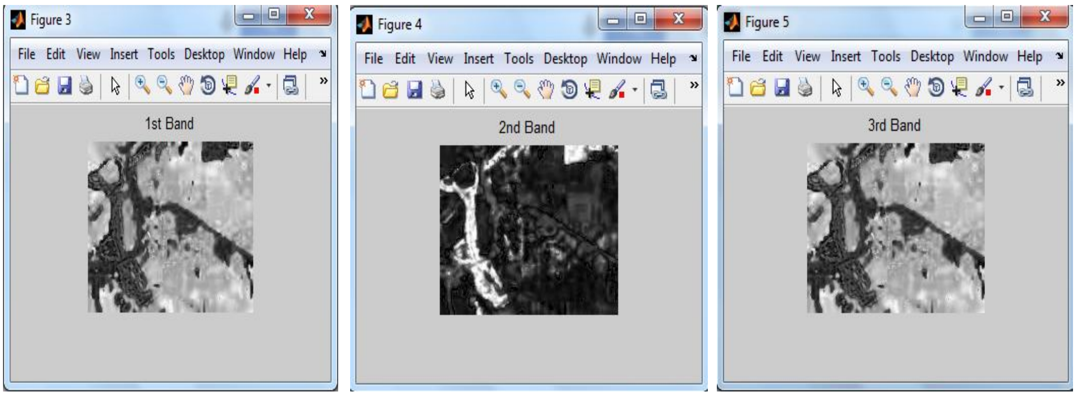

Figure (a) First Band **Figure (b) Second Band** **Figure (c) third Band**

Figure 4. 3 Feature Extraction Hyperspectral Images

Figure 3 shows that the extraction of features from original hyperspectral image. The hyperspectral images having set of sub bands. These sub bands are called features. These features are extracted from the original image.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

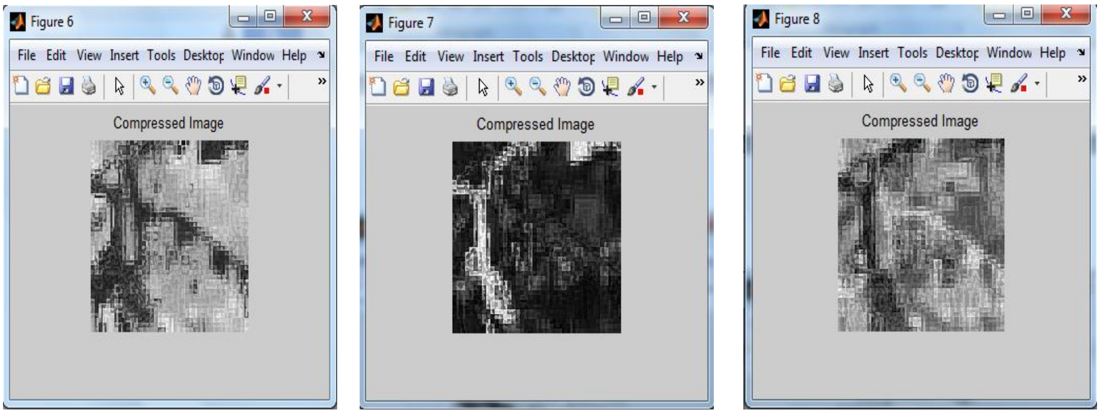

Figure 4.4 Compressed Feature Hyperspectral Images

Figure 4 shows that the extraction of features from original hyperspectral image. The hyperspectral images having set of sub bands. These sub bands are called features. These features are extracted from the original image. The extracted feature images are compressed using embedded block coding with optimized truncation method.

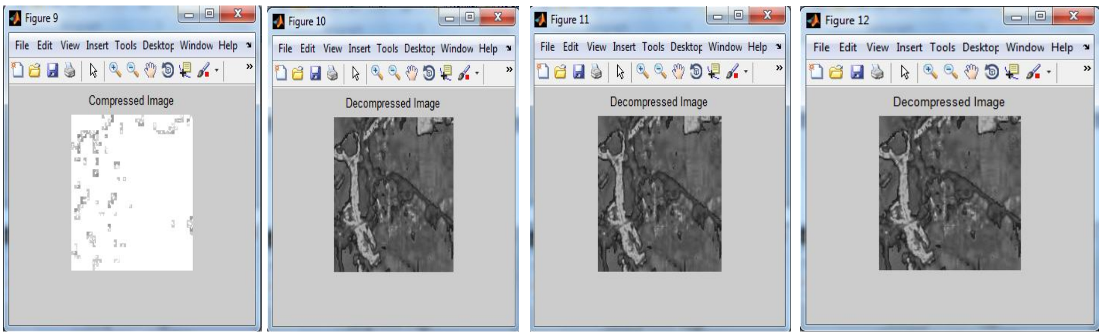

Figure 4. 5 Compressed Original Hyperspectral Image and Decompressed Feature Hyperspectral Images

Figure 5 represents the compressed image of original images with compressed feature images and the decompressed features images from the compressed feature images. The hyperspectral images having set of sub bands. These sub bands are called features. These features are extracted from the original image. The extracted feature images are compressed using embedded block coding with optimized truncation method. The compressed feature images are decompressed using the same method.

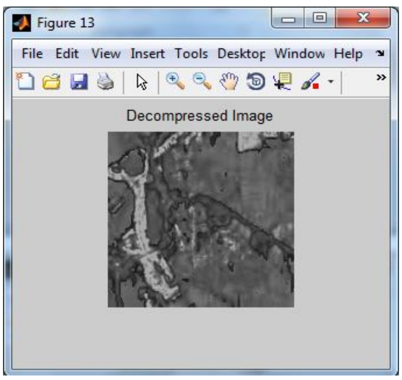

Figure 4.6 Decompressed Original Hyperspectral Image

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 7, July 2015

Figure 6 represents the decompressed image of original images with decompressed feature images. Figure 7 shows the reconstructed original image. The image is compressed and decompressed using embedded block coding with optimized truncation method. The image is reconstructed without losing of discriminant information.

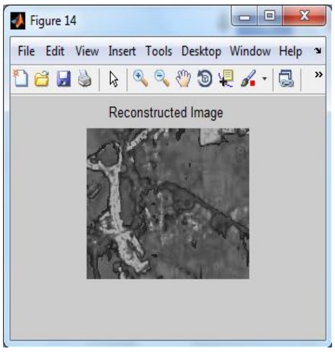

Figure 7 Reconstructed Hyperspectral Image

V. CONCLUSION

In this hyperspectral images based on embedded block coding with optimized truncation (EBCOT) along with encoding residual discriminant information is proposed. This scheme first applies a feature extraction method to obtain the feature images and then encoded the hyperspectral images using the dominant feature images. Then, it generates residual images by subtracting the reconstructed images from the original images. By applying EBCOT to the residual images, the discriminant feature images were compressed using conventional image compression techniques to achieve better performance Compressed hyperspectral bit streams require protection from channel errors during transmission.In the future, we will investigate this topic and implement appropriate channel coding algorithms.

REFERENCES

[1]Ian Blanes and Joan Serra-Sagristà, “Cost and Scalability Improvements to the Karhunen–Loeve Transform for Remote-Sensing Image Coding”, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 48, NO. 7, JULY 2010

[2]Pier Luigi Dragotti, Giovanni Poggi, and Arturo R. P. Ragozini “Compression of Multispectral Images by Three-Dimensional SPIHT Algorithm”, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 38, NO. 1, JANUARY 2000

[3]Barbara Penna, Tammam Tillo, Enrico Magli, and Gabriella Olmo, “Transform Coding Techniques for Lossy Hyperspectral Data Compression”, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 45, NO. 5, MAY 2007

[4]Marco Cagnazzo, Giovanni Poggi, and Luisa Verdoliva “Region-Based Transform Coding of Multispectral Images”, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 16, NO. 12, DECEMBER 2007

[5]Lena Chang, Yang-Lang Chang, Z. S. Tang, and Bormin Huang “Group and Region Based Parallel Compression Method Using Signal Subspace Projection and Band Clustering for Hyperspectral Imagery”, IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 4, NO. 3, SEPTEMBER 2011

[6]Xaoli Tang, William A. Pearlman_and James W. Modestino “Hyperspectral Image Compression Using Three-Dimensional Wavelet Coding” www.cipr.rpi.edu/staff/pearlman.html/papers/ tgars02_tp.pdf November 7, 2002

[7]Qian Du and James E. Fowler, “Hyperspectral Image Compression Using JPEG2000 and Principal Component Analysis”, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 4, NO. 2, APRIL 2007

[8]C. Lee and D. A. Landgrebe, “Analyzing high dimensional multispectral data,” *IEEE Trans. Geosci. Remote Sens.*, vol. 31, no. 4, pp. 792–800, Jul. 1993.

[9]G. Strang, *Linear Algebra and Its Applications*, 3rd ed. Tokyo, Japan: Harcourt Brace Jovanovich, 1988.

[10]S. Lim, K. Sohn, and C. Lee, “Principal component analysis for compression of hyperspectral images,” in. *Proc. IEEE IGARSS*, 2001, vol. 1, pp. 97–99.

[11]G. Vane *et al.*, “The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS),” *Remote Sens. Environ.*, vol. 44, no. 2/3, pp. 127–143, May/Jun. 1993.

[12] G. F. Hughes, “On the mean accuracy of statistical pattern recognizers,” *IEEE Trans. Inf. Theory*, vol. IT-14, no. 1, pp. 55–63, Jan. 1968.

[13]R. Gaetano, G. Scarpa, and G. Poggi, “Hierarchical texture-based segmentation of multiresolution remote-sensing images,” *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 2129–2147, Jul. 2009.

[14] J. Mielikainen and P. Toivanen, “Clustered DPCM for the lossless compression of hyperspectral images,” *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 12, pp. 2943–2946, Dec. 2003.

[15] J. Mielikainen and P. Toivanen, “Lossless compression of hyperspectral images using a quantized index to lookup tables,” *IEEE Geosci.Remote Sens. Lett.*, vol. 5, no. 3, pp. 474–478, Jul. 2008.

[16] O. M. Kosheleva, B. E. Usevitch, S. D. Cabrera, and E. Vidal, Jr., “Rate distortion optimal bit allocation methods for volumetric data using JPEG 2000,” *IEEE Trans. Image Process.*, vol. 15, no. 8, pp. 2106–2112, Aug. 2006.

[17] B. E. Usevitch, “A tutorial on modern lossy wavelet image compression: Foundations of JPEG2000,” *IEEE Signal Process. Mag.*, vol. 18, pp. 22–35, Sep. 2001.lk,