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HYBRID COMPRESSION OF HYPERSPECTRAL IMAGES BASED ON LINEAR DISCRIMINANT ANALYSIS

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Abstract—**The compression of Hyperspectral image (HSI) using more compression techniques. Most image compression based on Principle Component Analysis and it provides excellent Compression efficiency for Hyperspectral image. However, PCA doesn't capture all the discriminant information of HSI, since features that are important for classification tasks may not provide in high signal energy. To overcome this problem using Hybrid compression method for HSI with Pre-encoding discriminant information. First, Feature extraction method is applied to the taking original image then provides feature vector matrix, this matrix vector are generating the feature image. Then, compress the feature image we getting the compressed feature images and feature vectors and decoding process to the compressed images, we obtaining reconstruct original image. The residual image from the difference between the original image and reconstruct image, that residual image are again compressed by PCA getting compressed eigan image and mean image in encoding process. In Decoding process, both decoding compressed feature image data and decoding compressed eigan image data are added finally getting the decoded compressed image after transmitted in better compression efficiency with classification accuracy.**

Keywords—**feature extraction method Images, hyperspectral images, principal component analysis (PCA).**

I. Introduction

The advancement of sensor technology produces remotely sensed data that have a large number of spectral bands. There is an increasing need for efficient compression techniques for these hyperspectral images. Since adjacent bands of hyperspectral data are highly correlated, most compression techniques use this property to remove spectral redundancy: most lossless techniques resort to prediction, whereas most lossy techniques resort to transform-based approaches. In particular, in transform-based methods, principal component analysis (PCA) [also known as Karhunen–Loeve-transform(KLT)] has been commonly used, often followed by 2D transforms such as the discrete wavelet transform (DWT) or the discrete cosine transform (DCT).Wavelet transform-based methods have drawn great interest, too and a number of 2-D wavelet based techniques have been extended to 3-D applications, including set partitioning in hierarchical trees (SPIHT), set partitioning embedded block (SPECK), and tarp coding. In addition, JPEG2000 standard allows compressing hyperspectral images with arbitrary spectral decorrelation. Region-based coding schemes have been studied, too, often yielding improved SNR performance. Most lossy compression methods have been developed to minimize mean squared errors between the original and the reconstructed pixels. As an example, JPEG2000 coders coupled with spectral PCA produce good performance in terms of SNR, but their classification accuracy may not be satisfactory 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 letter, we propose a hybrid compression method that takes into account the discriminating information of hyperspectral images. First, we apply a feature extraction method to obtain feature images, which are then used to generate feature are constructed images. These feature-reconstructed images are subtracted from the original images to produce residual images. The feature images and some eigen images of the residual images are compressed using conventional compression techniques.

Therest of this letter is organized as follows. The feature extraction and the feature images are introduced, along with the proposed PCA-based compression method with pre-encoding discriminant information.

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II.COMPRESSION TECHINIQUES

A.*Principal behind compression*

A communal characteristic of most images is that the adjacent pixels are correlated and therefore contain redundant information. The foremost task then is to discover less correlated representation of the image. Image compression addresses the trouble ofreducing the quantity of data essential to represent a digital image. The underlying basis of the reduction process is the elimination of redundant data. From a mathematical viewpoint, this amounts to transforming a 2-D pixel collection into a statistically uncorrelated information set. The conversion is applied past to storage and transmission of the image. The compressed image is decompressed at some delay, to reconstruct the original image or an approximation to it. Two basic components of compression are redundancy and irrelevancy reduction. **Redundancy reduction** aims at removing duplicate data from the signal source (image/video). **Irrelevancy reduction** omits parts of the signal that will not be showing by the signal receiver, namely the Human Visual System (HVS). In general, three types of redundancy is,

- **Spatial Redundancy** or correlation between neighboring pixel values.
- **Spectral Redundancy** or correlation between different color planes or spectral bands.
- **Temporal Redundancy** or correlation between adjacent frames in a sequence of images (in video applications).

Image compression aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as achievable.

B.Di*fferentclassesofcompressiontechniques*

Two ways of classifying compression techniques are mentioned here**.**

(i).**Lossless vs. Lossy compression:** In lossless compression schemes, the reconstructed image, after compression, is numerically equal to the original image. However lossless compression can only achieve a modest amount of compression. An image reconstructed following lossy compression holds degradation relative to the original. Frequently this is because the compression scheme totally discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under usual viewing conditions, no visible loss is perceived (visually lossless).The information loss in lossy coding originates from quantization of the data. Quantization can be defined as the process of arrangement the data into different bits and representing each bit with a value. The value selected to characterize a bit is called the reconstruction value. Each item in a bit has the same reconstruction value, which mains to information loss (unless the quantization is so fine that every item gets its own bit).

ii**). Predictive vs. Transform coding:** In predictive coding, data already sent or available is used to predict future values, and the difference is coded. Then this is done in the image or spatial domain, it is relatively simple to implement and is readily modified to resident image characteristics. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the additional hand, first transforms the image from its spatial domain representation to a dissimilar type of representation using some famous transform and then codes the transformed values (coefficients). This method offers greater data compression compared to predictive methods, although at the expense of greater computation.
Fig (1).

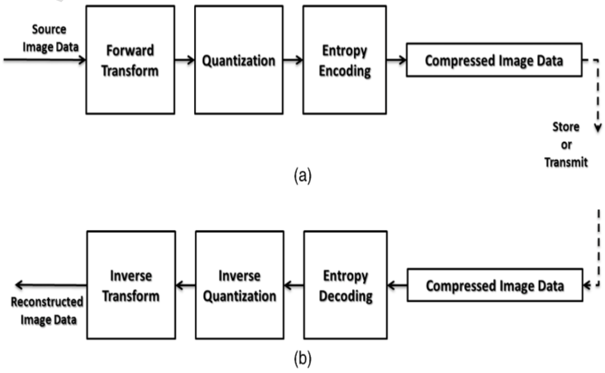

Fig (1).Basic function of Compression

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From the fig (1), A variety of linear transforms have been established which include Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and many more, each with its own benefits and drawbacks.

A quantizer basically reduces the number of bits needed to store the transformed quantities by reducing the exactness of those values. Since this is a many-to-one charting, it is a lossy process and is the main basis of compression in an encoder. Quantization can be done on each individual coefficient, which is known as Scalar Quantization (SQ). Quantization canalso be done on a group of coefficients together, and this is known as Vector Quantization (VQ). Together uniform and non-uniform quantizers can be used subject on the problem at hand. An entropy encoder additional compresses the quantized values losslessly to offer better overall compression. It uses a classic to precisely determine the possibilities for each quantized value and produces an appropriate code based on these probabilities so that the resulting output code stream will be smaller than the input stream. The most frequently used entropy encoders are the Huffman encoder plus the arithmetic encoder, though for applications requiring fast execution, simple run-length encoding (RLE) has established very effective. It is significant to note that a appropriately designed quantizer and entropy encoder are absolutely essential beside with optimal signal transformation to get the best possible compression.

III.ARCHITECTURE OVERVIEW

Compression method are used to reduce the storage space and transmission bandwidth in the digital image processing. Image compression is reducing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size permits more images to be stored in a given amount of disk or memory space. It furthermore reduces the time required for images to be sent over the Internet or downloaded from Web pages. There are several different methods in which image files can be compressed. The hybrid compression techniques are used in the hyperspectral image and this compression having encoding and decoding process with diagram shown in below:

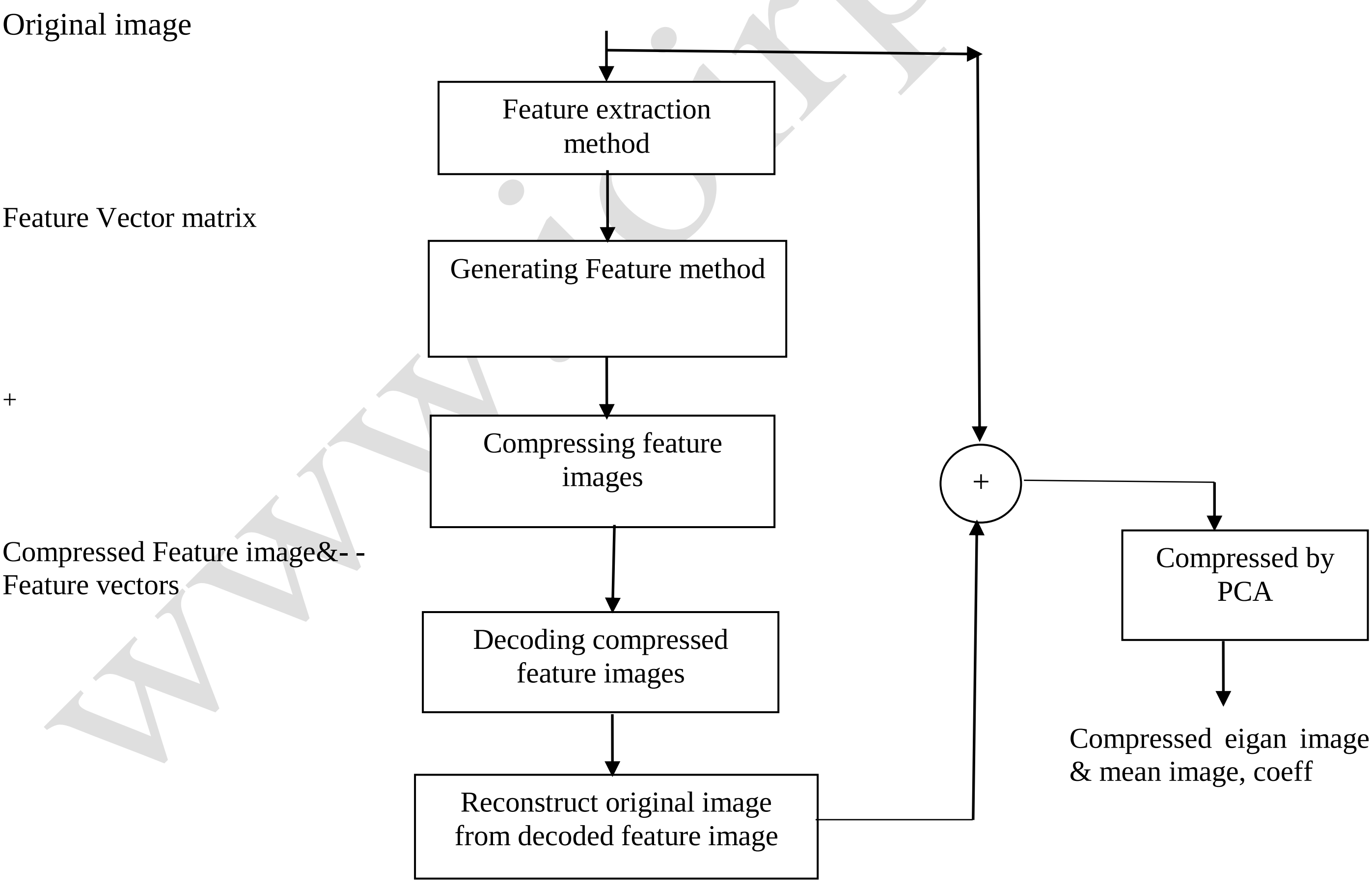

Fig (2). PCA encoding method diagram

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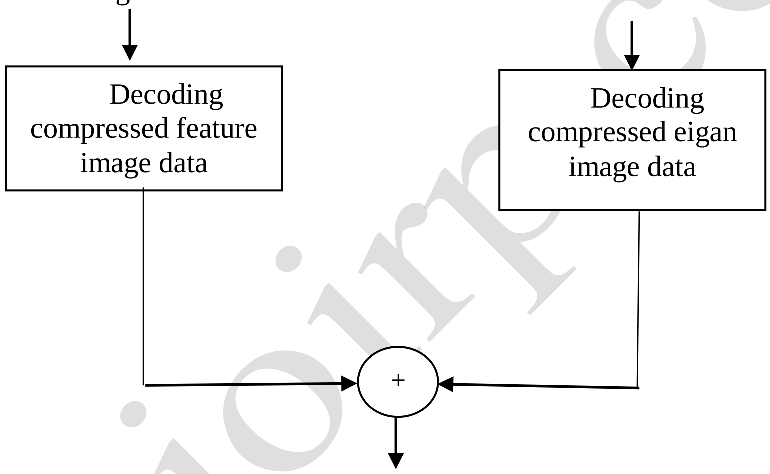
Most image compression based on Principle Component Analysis and it offers good Compression efficiency for Hyperspectral image. The Hybrid compression method for Hyperspectral Image with Pre-encoding discriminant information. First, Feature extraction method is applied to the takingoriginal image then provides feature vector matrix, this matrix vector are generating the feature image. Thencompress the feature image, I getting the compressed feature images and feature vectors and decoding process to the compressed images, we obtaining reconstruct original image. The residual image from the difference between the original

image and reconstruct Image, that residual image are again compressed by PCA getting compressed eigan image and mean image in encoding process fig (2).

Compressed feature image &
Feature vectors

Compressed eigan &
mean image and coeff



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Reconstruct image

Fig (3).PCA decoding method diagram

In fig (3) Decodingprocess, both decoding compressed feature image data and decoding compressed eigan image data are added finally getting the decoded compressed image. Finally getting this reconstruct image from the decoded compressed images are transmitted in better compression efficiency with classification accuracy.

IV.PERFORMANCE EVALUATION

Compression efficiencyis measured by the compression ratio and is estimated by the ratio of the original imagesize over the compressed data size. The complicationof an image compression process is calculated by the number of data operations required to execute both encoding and decoding processes. Practically, it is sometimes expressed by the number of operations. For a lossy compression method, a *distortion measurement* is a criterion for determining how much data has been lost when the reconstructed image is formed from the compressed data. The most frequently used measurement is the mean square error (MSE).In the MSE measurement the totalsquared difference between the original signal and the reconstructed one is averaged over the entire signal. Mathematically,

$$\textbf{MSE} = \frac{1}{N}\sum_{i=0}^{N-1}(\hat{x}_i - x_i)^2$$

where $\hat{x}_i$ is the reconstructed value of x_i .N is the number of pixels. The mean square error is commonly used because of its

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Convenience. A measurement of MSE in decibels on a logarithmic scale is the Peak Signal-to-Noise Ratio (PSNR), which is a popular standard objective measure of the lossy codec. We use the PSNR as the objective measurement for compression algorithms throughout this thesis. It is defined as follows,

$$PSNR = 10\log \frac{MAX^2}{\frac{1}{w \times h}\sum_{i=1}^{w}\sum_{j=1}^{h}(o(i,j)-c(i,j))^2}$$

Where *w*and *h*are the width and height of the image respectively, o is the original image data, and c is the compressed image data. MAX is the maximum value that a pixel can have, 255.

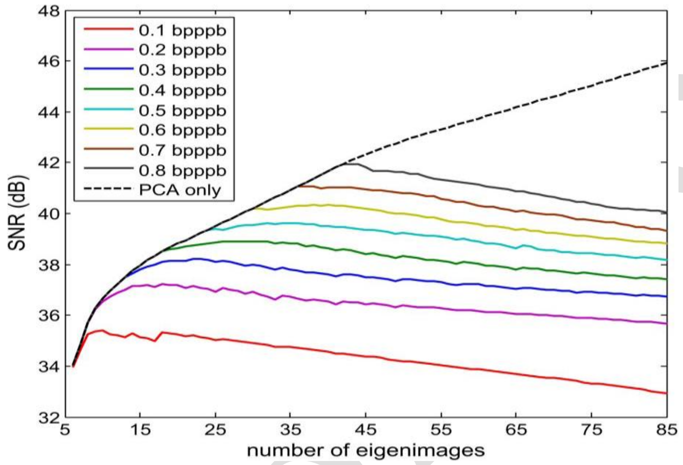
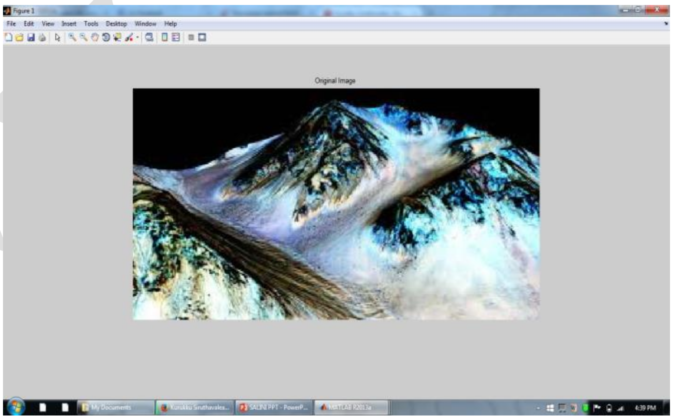


Fig (4) .SubPCA/1-D + 2-D JPEG2000

V. SIMULATION RESULT



5.1. Original image

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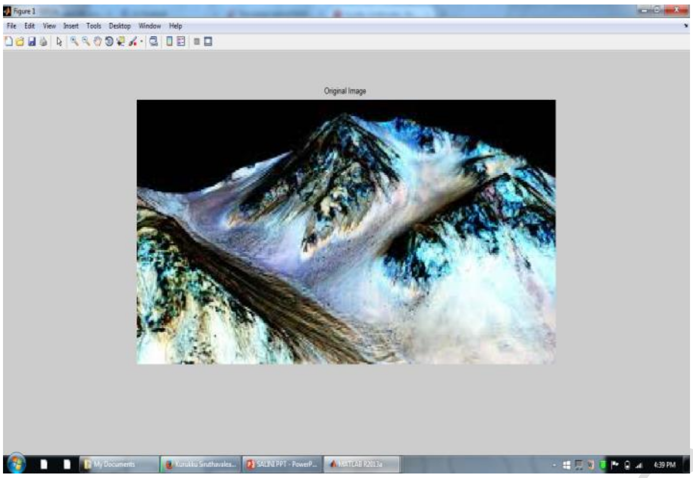
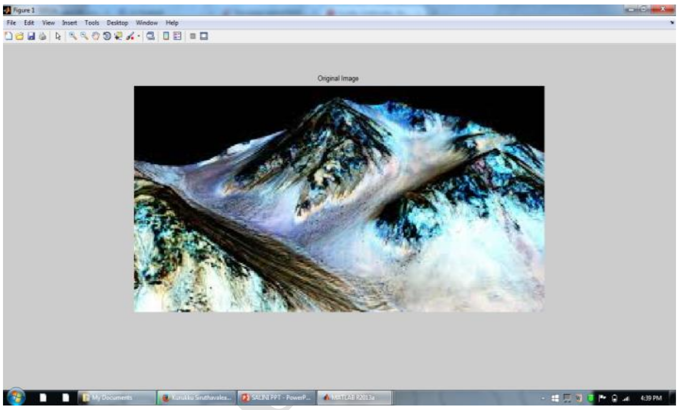
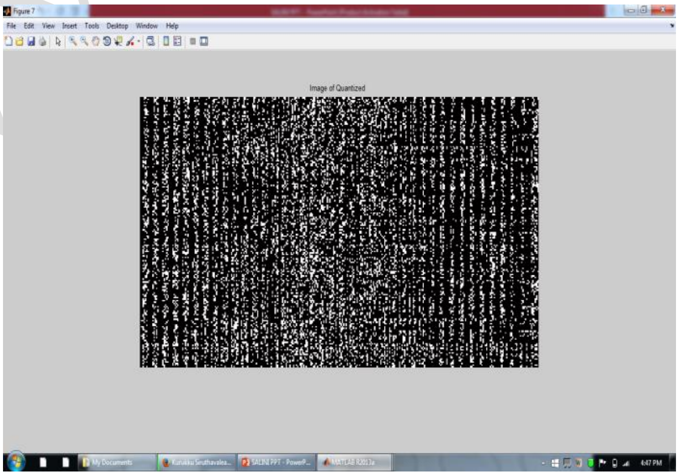


5.2. HSI image



5.3. Image to lapped orthogonal transform



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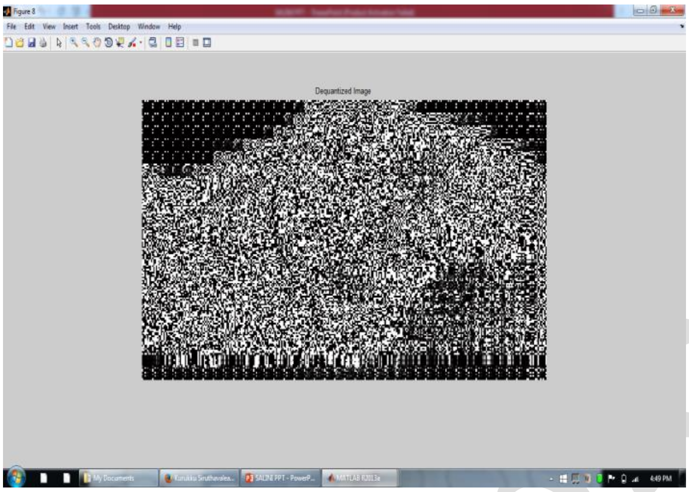
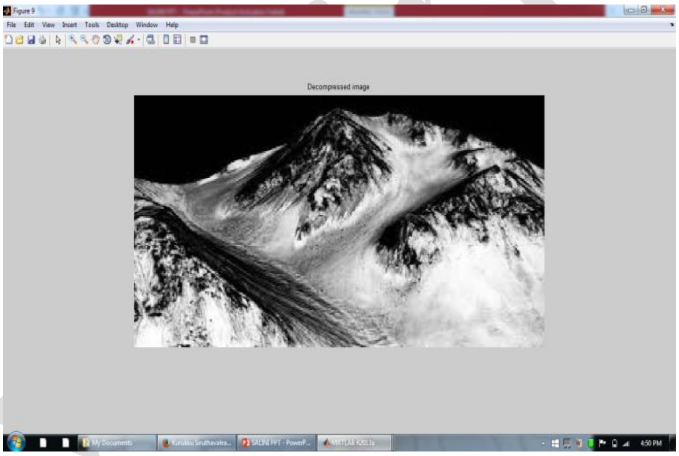
5.4. Image Quantize



5.5. Image Dequantized



5.6. Decompressed image

PSNR value=37.72db

Compression ratio=66.67%

VI.CONCLUSION AND FUTURE WORK

The results of mentioned method of compression using PCA can be a suitable choice to compress images. The speed of the algorithm can be increased with parallel programming. Because the compression process of the various bands of the image are independent with each other. The other advantage of this method is the short time of reconstruction of compressed images and Hybrid compression method for hyperspectral images based on PCA to achieve better performance.

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Further improvements of Hybrid compression for HSI by using LDA system especially in terms of speed can be achieved by introducing a lattice factorization of the wavelet kernel. This will reduce the computational complexity and complement the memory reductions.

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