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Comparison between the parameter values of EBCOT pre encoding technique on hyperspectral band clustering with EBCOT post encoding technique

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ABSTRACT

The image compression based on Pre - encoding based EBCOT (PRE-EBCOT) provides better efficiency in terms of compression for hyperspectral images. However, PRE-EBCOT method might fail to determine all the characteristics of hyperspectral images. To deal with this problem, a hybrid compression method namely, Post-encoding based EBCOT (POST-EBCOT) is proposed for hyperspectral images with post-encoding discriminant information. First, the extraction of features method is applied to the input images and provides vectors of feature set which are used to generate feature images and remaining (i.e residual) part of images after extracting the features are obtained by subtracting the reconstructed feature images from the input. Both feature and residual images are compressed and transmitted. Here the results of EBCOT post-encoding on hyper spectral band clustering is compared with the results with EBCOT pre-encoding technique and the parameter value indicates that the proposed EBCOT post-encoding method provides better compression efficiency with improved classification accuracy than conventional compression methods.

KEY WORDS: PCA, Pre encoding, Post encoding, EBCOT.

1. INTRODUCTION

The region-based coding schemes have been studied that often yielding improved SNR performance. Also most lossy compression methods are introduced in order to reduce the MSE between the input (i.e original) and the reconstructed (i.e retrieved after decompression) pixels. However, a characteristic information is needed to distinguish between the various methods are also important for applications based on classification purposes. 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 does not have high energy.

In this paper, a hybrid compression method called, POST-EBCOT is presented for hyperspectral images with post-encoding discriminant information. First, extraction of feature method is applied to the input images that producing vectors of feature set that are used to generate feature images and then remaining (i.e residual) images are obtained by calculating the difference between the reconstructed feature images from the input. Then feature 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 results prove that the POST-EBCOT method has high SNR value, efficiency, compression ratio and low MSE.

Post Encoding Based EBCOT: 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 $|c|\geq 2p$. 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 models of context are used by magnitude refinement pass to encoding the value of sample only if it is already significant in the current bit-plane p.

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 POST-EBCOT (Modified POST EBCOT) algorithm is needed to overcome this above problem, which can be solved by dividing each three dimension sub-band into small three dimensional 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 $a\times a\times a$ samples and describe a specific region of the 3-D image at a specific decomposition level.

The size of the cube is defined by employing a pyramid approach across the different decomposition levels. The size of code cube be $z\times z\times z$ samples and {a, b, c} be the position at decomposition level d is related to a code-cube of size samples z/2×z/2×z/2 and position {a, b, c} at decomposition level d+1, where d=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 three dimensional image at any resolution. Here the dimension of code-cube limited to the power of 2 and it codes each code-cube using a modified EBCOT with three dimensional contexts independently.

Coding wavelet coefficients by extending two dimensional context modeling to three dimensional has been extensively used to improve coding efficiency. Here, POST-EBCOT method uses context model with three dimension based on the coding process which incorporates information from the immediate temporal neighbors of sample located in the direction of horizontal, diagonal and vertical slices. The sample significance is highly dependent upon the immediate neighbors in vertical, horizontal and diagonal direction. Here, in order to make full use of correlations of inter slice, the information about nearest temporal neighbors is employed.

2. PROPOSED SYSTEM

Feature Extraction and Feature Images: Linear feature extraction can be viewed as a linear transform. The extraction of feature method produces vectors of feature set {βi}, and an extracted feature is computed as follows:

$$y_i = \beta_i^T X \qquad (1)$$

Where X represents an observation in the N-dimensional space. In most cases, the vectors of feature set {βi} may be considered as orthonormal. Several methods are used for extraction of features for pattern classification in the past. 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. The invertible covariance matrices are used in most feature extraction methods. But the covariance matrix produced by hyperspectral images may not be invertible because of high correlations between adjacent bands and with a large number of training samples. To deal with this, this compression method uses the band combination procedure and the band expansion method.

Figure.1 shows a block diagram of the POST-EBCOT compression method. This method assumes that the original images contained N spectral bands and K pixels in each band. We let $J_1, J_2, . . . , J_N$ be the N spectral bands, where Ji was a K × 1 column vector. For notational convenience, these vectors were presented in a K × N matrix, i.e., $J = [J_1, J_2, . . . , J_N]$.

First, we apply extraction of feature to the input images based on a set of given classes. This process will produce a set of feature vectors. It is assumed that the vectors of feature set forms an orthonormal basis. In this case, the following feature vector matrix can be viewed as a unitary transform:

$$B = [\beta_1, \beta_2, . . . , \beta_N] \qquad (2)$$

Where βi is an N × 1 column vector. Let X be a pixel vector of the original image, which corresponds to each column vector of JT.

Figure.2, 3 shows that the comparison graphs of mean square error (MSE) and Peak Signal to Noise Ratio (PSNR) between PCA and EBCOT. PSNR is defined as the ratio between the maximum signal power and noise power. It is expressed in terms of decibel. PSNR measures the quality of reconstructed images. The signal power represents the input data and the noise represents the error due to compression. Although a higher PSNR generally indicates that the reconstruction of better quality, in some cases it may not. The graph represents that the proposed EBCOT method provides high PSNR value and low MSE than PCA.

Compression ratio is defined as reduction rate of data size produced by a compression algorithm. It is defined as the ratio of uncompressed data size to compressed data size.

Figure.4 shows that the comparison graphs of compression ratio between PCA and EBCOT. The compression ratio is higher when compared to PCA. Figure.5 shows that the comparison graphs of efficiency between PCA and EBCOT. The efficiency of EBCOT is 80 percent which is higher than that of PCA which has 50 percent.

The table.1 represents the parameters values in PCA and EBCOT. From this the proposed EBCOT method has high efficiency, compression ratio, PSNR and low MSE. Figures.6, 7 shows that the comparison graphs of MSE and PSNR between PCA, pre-EBCOT and post-EBCOT. The graph represents that the proposed post EBCOT method provides high PSNR value and low MSE than PCA. Compression ratio is defined as the ratio between the size of uncompressed data and size of compressed data.

Table.1.Parameter values

Parameters	PCA	PRE-EBCOT
Efficiency (%)	50	80
Compression Ratio (%)	30	74
Mean Square Error	2.6	4.5
Peak Signal to Noise Ratio	30	62

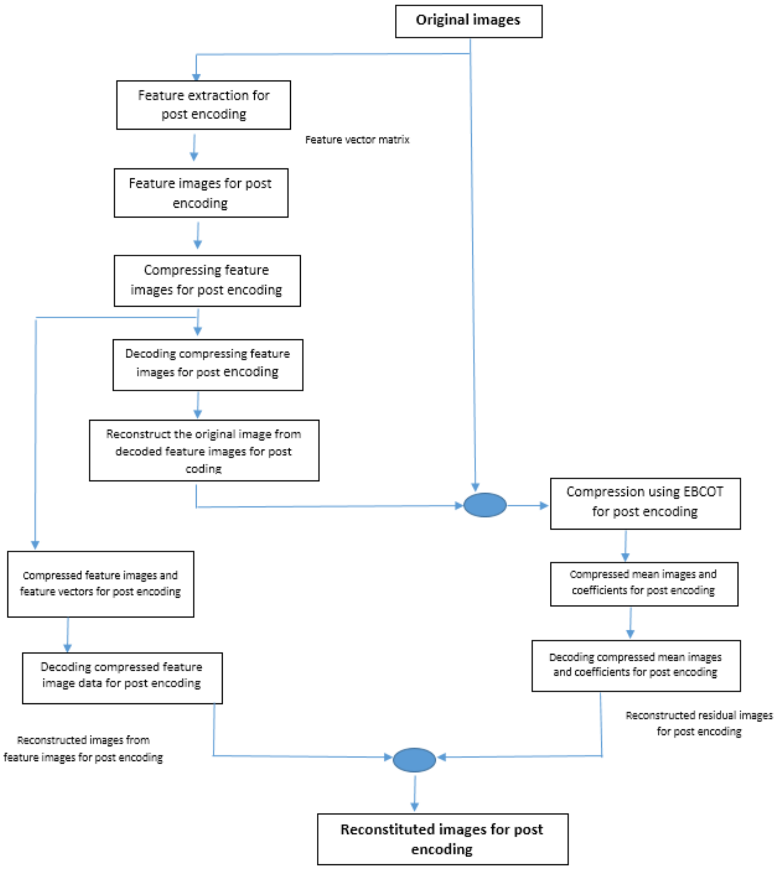

Figure.1.Block diagram of post EBCOT compression method a)encoding b)decoding

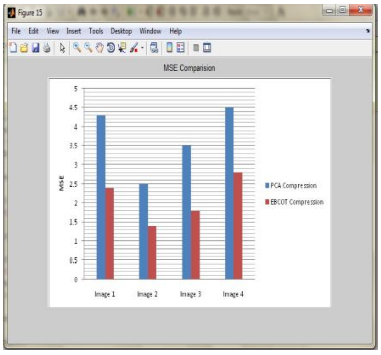

Figure.2.Comparison graph for MSE (mean square error)

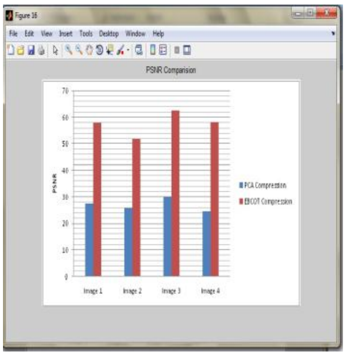

Figure.3.Comparison graph for PSNR (Peak Signal to Noise Ratio)

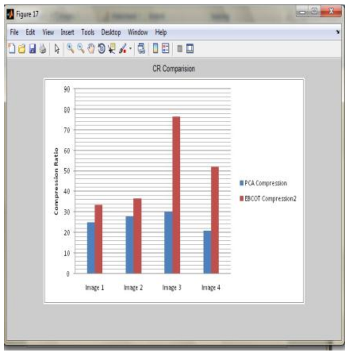

Figure.4.Comparison graph for Compression ratio

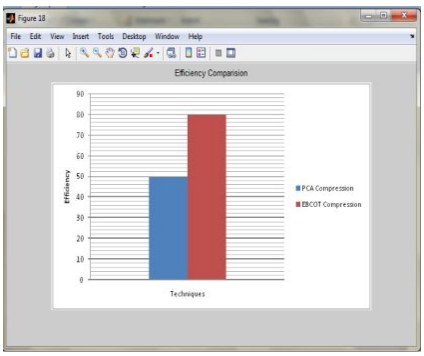

Figure.5.Comparison graph for efficiency

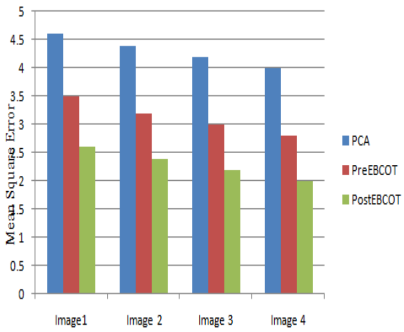

Figure.6.Comparison graph for MSE (mean square error)

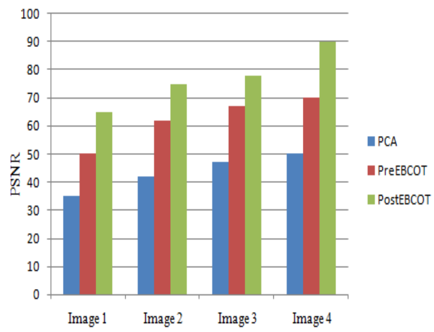

Figure.7.Comparison graph for PSNR(Peak Signal to Noise Ratio)

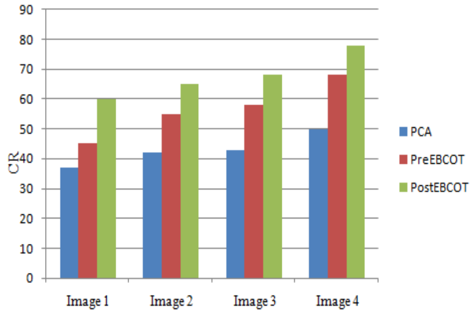

Figure.8.Comparison graph for Compression ratio

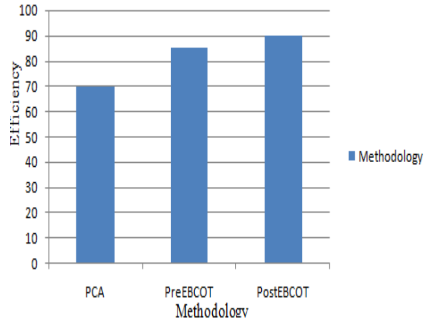

Figure.9.Comparison graph for efficiency

Figure.8 that the comparison graph of compression ratio between PCA, pre EBCOT and post EBCOT. The compression ratio is higher when compared to PCA. Figure.9 shows that the comparison graph of efficiency between PCA, pre EBCOT and post EBCOT. The efficiency of post EBCOT is 80 percent which is higher than that of PCA which has 50 percent.

Table.2.Parameter values

Parameters	PCA	Pre EBCOT	Post EBCOT
Efficiency (%)	60	80	90
Compression Ratio (%)	47	64	78
Mean Square Error	4.5	3.5	2.6
Peak Signal to Noise Ratio	45	55	78

The table 2 represents the parameters values in PCA, pre EBCOT and post EBCOT. From this, the post EBCOT method has high efficiency, compression ratio, PSNR and low MSE.

3. CONCLUSION

In this Hyperspectral image pre EBCOT and post EBCOT. Compared to pre encoding, post EBCOT method has high efficiency, compression ratio, PSNR and low MSE.

Experiments with AVIRIS showed that the proposed method produces better compression efficiency with improved classification accuracy than existing compression methods such as 1-Dimensional, 2-Dimensional JPEG2000 and subPCA/1-Dimensional, 2-Dimensional JPEG2000. Experiments results indicate that the proposed method provides better compression efficiency with improved classification accuracy than conventional compression methods. In this Hyperspectral image pre Encoding EBCOT and post Encoding EBCOT are included when compared the pre Encoding EBCOT, The Post Encoding EBCOT method has high efficiency, compression ratio, PSNR and low MSE.

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