Enhancement of Dynamic Encoded Multispectral Images for Effective Visualization

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Abstract

The paper proposes a novel method which dynamically encodes the multispectral images followed by image enhancement. The compression or encoding of images works with its unique spectral characteristics. The encoding algorithm shows its performance on the basis of image content. An image can be categorized as semantic classes or datatype classes. Semantic classes are nothing but the regions like clouds, mountains, rivers etc. Datatype classes are smooth regions and textured regions. If a particular region of interest is concerned for the application, semantic classes are exposed and compressed. The proposed work concentrates on datatype classes. Initially Principal Component Analysis and Wavelet transformation are carried out in the spatial and spectral domain respectively. The transformed image is then segmented into smooth and textured regions. Based on the region, compression technique is applied dynamically. SPIHT is used for smooth regions since it well suits for images with more smooth regions and similarly wavelet method for textured regions thereby incorporating the advantages of both the algorithms. A variety of enhancement techniques are applied to the compressed image and the results are compared using the metrics WQM and CEF.

Keywords: Principal Component Analysis, Wavelet, Dynamic encoding, WQM, CEF

1. Introduction

Multispectral images are the main type of images acquired by remote sensing radiometers. Since it includes more details and more spectral bands, the size of a multispectral image is very high. Ground stations acquire and use such images for a variety of applications like vegetation, geology, mining etc. There comes the importance of compression. Only compressed images can be manipulated by end users.

The existing compression algorithms do not consider the spectral characteristics [2] which are unique to multispectral images. The proposed work transforms the image using Wavelet inspectral domain and Principal component analysis in spatial domain.

Transformation plays a key role in the success of efficient compression. It packs as much information as possible into the smallest number of transform coefficients. Among the transformations like Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), Walsh Hadamard Transform (WHT), the information packing ability of the DCT is superior to that of the DFT and WHT. Although this condition holds for most images, P.J.Reddy and Wintz [19] showed that the KarhunenLoeve Transform (KLT) is the optimal transform in an information packing sense for multispectral images. Initially the transformation [6] is applied only in spatial domain. Later, to improve the performance, both spatial and spectral domains [21] are considered. Recently the transformation is adapted to local image content and thereby uses the concept, adaptive transformation.

The transformation is followed by quantization if the compression is lossy. Such encoding techniques come under vector quantization [17]. Based on some predicted values for the pixels, encoding can be done in predictive coding. Depending on the application and system constraints, any particular coding algorithm like arithmetic coding, Huffman coding, ziv-lempel coding, wavelet coding, SPIHT [18, 23], Hilbert scanning is selected.

The encoding algorithm shows its performance on the basis of image content. An image can be categorized as semantic classes or datatypeclasses [4]. Semantic classes are nothing but the regions like clouds, mountains, rivers etc. Datatype classes are smooth regions and textured regions. If a particular region of interest is concerned for the application, semantic classes are exposed and compressed.

The paper deals with datatype classes since the whole image (not a particular region) is considered for compression. In the research work, the image decomposition is based on the statistical feature, transformation by Principal Component

ISSN: 2349 - 6363

transform and the encoding is by two different algorithms based on the regions identified. SPIHT is used for smooth regions since it well suits for images with more smooth regions and similarly wavelet [5] method for textured regions thereby incorporating the advantages of both the algorithms. Multispectral images can be acquired from [24].

The organization of paper is as follows. Section II describes transform coding where the image is decomposed into smooth and textured regions and transform selection. Section III describes the dynamic encoding technique. Section IV enhances the compressed image for better and effective visualization and deals with results and discussion. Various enhancement techniques are used and results are compared using the metrics WQM (Wang's Quality Metric) and CEF (Color Enhancement Factor). Section V concludes the work and proposes future work.

2. Transformation

Transformation decorrelates the spectral and spatial coefficients which in turn makes the compression efficient. Images can be split based on segmentation. The segmentation may be pixel based or region based. The image is decomposed into datatype classes based on the statistical measure, standard deviation. If standard deviation is zero, it belongs to smooth class/region and if not, textured class/region. Transformation is then applied to the regions which maps the region into a set of transform coefficients which are then encoded.

Fig 1 shows a typical transform encoder. It involves three relatively straightforward operations: transformation, segmentation and encoding. The goal of the transformation process is to decorrelate the pixels of each region, or to pack as much information as possible into the smallest number of transform coefficients.

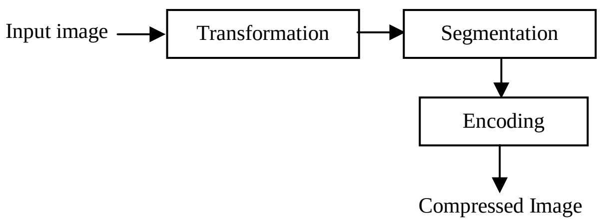

Fig.1 Transform Encoder

The transformation can be adapted to local image content, called adaptive transform coding, or fixed to the whole image called nonadaptive transform coding.

2.1. Principal Component Analysis

The choice of a particular transform in a given application depends on the amount of reconstruction error that can be tolerated, the computational resources available and the type of images considered. Principal Component Analysis is well suited for multispectral images. It is also termed as hotelling transform. It is a signal-dependent transform [8] that decorrelates the signal. It is a diagonalization matrix for the auto covariance matrix of the signal. Let us denote the signal vector of 'n' data points by x (n x 1matrix). The auto covariance matrix R is defined as

$$R=E[(x-\mu)(x-\mu)^T]$$

where $\mu = E[x]$

Without loss of generality, we can assume $\mu=0$

The autocovariance then becomes

$$R = E[xx^T] \qquad (1)$$

Since R is real symmetric matrix, it can always be diagonalized. Thus, there exists an orthonormal matrix M such that

$$M^TRM = D \qquad (2)$$

where D is a diagonal matrix corresponding to the eigenvalues of the matrix R. Note that each column of M is an eigenvector of R.

The KLT is defined as

$$y=M^Tx \qquad (3)$$

The transform has a nice property that the transformed vector y is decorrelated. The hotelling transform is optimal in the sense that it minimizes the mean square error between the vectors x and their approximations y. From (1), we have

$$E[yy^T]=E[M^Txx^TM]=M^TE[xx^T]M=M^TRM \qquad (4)$$

Thus, using (2)

$$E[yy^T] = D \qquad (5)$$

To obtain the KLT matrix M^T, we need to solve for the eigenvectors of R. Jacobi transformation algorithm [9] is used to solve Eigen vectors. The algorithm is based on the following successive similarity transformation. The transformation is defined as

$$R^T = P^TRP \qquad (6)$$

where R^T is a transformed matrix and $P = P_1P_2P_3\ldots$. Each $P_i(i=1,2,\ldots)$ is a orthonormal similarity transformation. With proper choice of P_i, R^T converges to a diagonal matrix which is none other than the matrix of the desired eigen values and P becomes the eigenvector matrix.

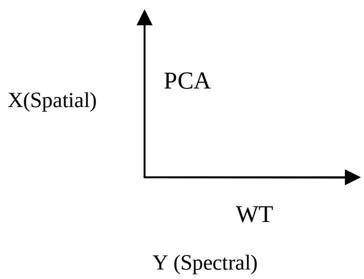

Fig. 2 WT for the spectral domain and PCA for the spatial domain

The error can be minimized by selecting the k eigen vectors associated with the largest eigen values. Hotelling transform is optimal in the sense that it minimizes the mean square error between the vectors x and their approximations y.. The PCA is applied only to the spatial domain in the imagery whereas the Wavelet Transform [13] is applied to the spectral domain as shown in Fig. 2.

2.2. K Means Clustering

Pixel based segmentation consider image segmentation as a labeling issue at pixel level. A region can be described by quantifying its texture content. The three principal approaches used in image processing to describe the texture of a region are statistical, structural and spectral. Statistical approaches yield characterizations of textures as smooth, coarse, grainy and so on. Structural techniques deal with the arrangement of image primitives, such as the description of texture based on regularly speed parallel lines. Spectral techniques are based on properties of the Fourier spectrum.

Since, the proposed work concentrates on smooth and textured regions, statistical approaches are used to define the region. The standard deviation is used frequently as a measure of texture. It is 0 for areas of constant intensity and is greater than zero for textured regions. K-Means [1] is an *exclusive clustering* algorithm. It involves pixel based segmentation.

i. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
ii. Assign each object to the group that has the closest centroid.
iii. When all objects have been assigned, recalculate the positions of the K centroids.
iv. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

The K-Means algorithm does not necessarily find the most optimal configuration. Since PCA has been applied prior [19], it results in optimal solutions.

Fig. 3(a) Multispectral Image (b) Smooth Regions (c) Textured Tegions

The multispectral image of Little Colardo River is shown in Fig 3(a) Using K-Means Clustering, the image has been clustered into two regions, smooth and textured. Fig 4(b) and (c) show the smooth and textured regions respectively.

2.3. Bit Allocation

The reconstruction error associated with the truncated series expansion of region splitting and transformation is a function of the number and relative importance of the transform coefficients that are discarded, as well as the precision that is used to represent the retained coefficients. In most transform coding systems, the retained coefficients are selected on the basis of maximum variance, called zonal coding [15], or on the basis of maximum magnitude, called threshold coding. The overall process of truncating and coding the coefficients of a transformed sub image is commonly called bit allocation. The transform coefficients of maximum variance carry the most information and should be retained in the coding process.

Bit allocation, either explicit or implicit, is a critical part of any transform coding technique. The class based approach can be convenient in a rate-distortion sense for the compression of the whole image. Bit allocation has the goal of obtaining the least possible overall distortion for the assigned resources. Lagrangian optimization says that an optimal allocation is reached when each encoding bit produces the same decrease in distortion on any region.

3. Dynamic Encoding Technique

Various compression algorithms like JPEG compression algorithm, object based wavelet method etc on spectrally homogeneous regions are discussed by Maria Petrou, Hou, Sei-ichiroKamata, and Craig [16]. The multispectral image is divided into many regions and adaptive transformation is applied. The encoding algorithm is then applied to the transformed coefficients.

If some particular regions are considered as regions of interest [12], then encoding is applied to those regions only and other regions are not considered for compression. Based on the application [20], suitable compression algorithm is selected and applied.

For example, if the region of interest is relatively uniform like flat area, water area etc., SPIHT [18] is applied. If the ROIs are highly textured [11], e.g., mixed fields area, mountain area, the wavelet method is applied.

Separable filters [22] are used to decompose the given arbitrarily shaped object into four subbands (LL, LH, HL andHH), then the LL band is further decomposed. At each decompositionlevel, the signal is properly extended and downsampled so that the original signal with length *N* is represented by the same number of wavelet coefficients with perfect reconstruction property.

The paper proposes a new adaptive encoding technique which is based on the datatype classes[14] identified in the image.

The semantic classes in an image say about the objects involved in the image. The datatype classes deal with the texture content. If the texture is uniform, the region is said to be smooth and if not, the region is said to be highly textured. Fig 4 explains the proposed work.

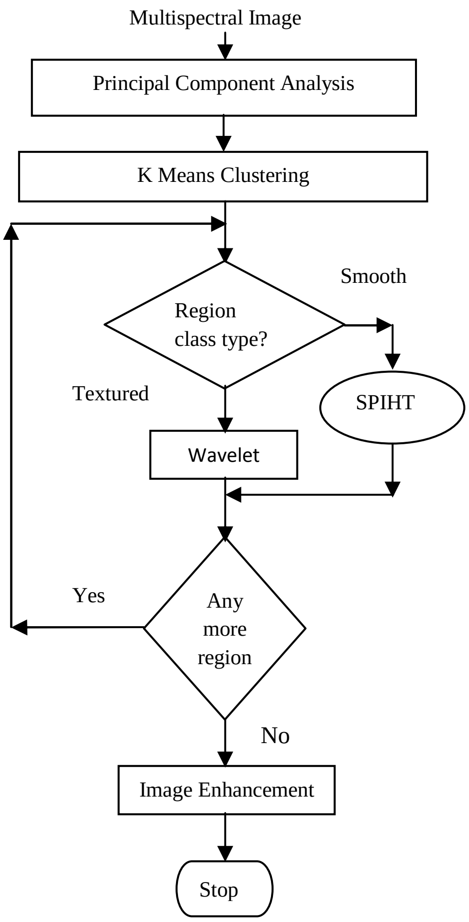

Fig. 4 Class Based Multispectral Encoding

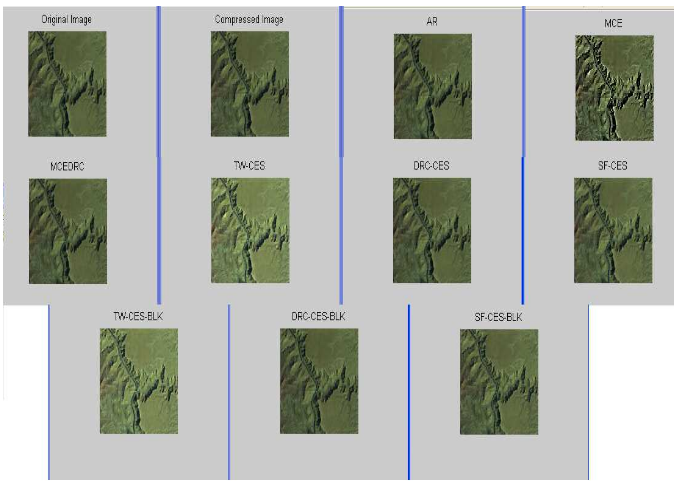

Fig. 5 (a) Original Image (b) Compressed Image (c) – (k) Enhanced Images

The image is decomposed into its datatype classes based on the standard deviation. The resultant classes are smooth and textured. If the region is smooth, SPIHT is applied. If the region is textured, wavelet encoding is applied. Thus in a single image, the advantages of both the algorithms are incorporated.

4. Results and Discussion

The goal of the image enhancement is to improve the visual appearance of the image, or to provide "better" transform representation for future automated image processing (analysis, detection, segmentation, and recognition).

Various enhancement [10] techniques like alpha-rooting, multicontrast enhancement technique [9], and multicontrast enhancement coupled with dynamic range compression, DCT techniques [7] with and without blocking artifacts etc. are applied in the compressed image. The resultant images are thereby, then, compared using Wang's quality metric and Color Enhancement Factor.

Table 1 Various Enhancement methods and the results

Enhancement Method	Wang's Quality Metric	Color Enhancement Factor
MCE	8.15	0.99
MCEDRC	6.73	1
AR	7.36	1
TW-CES	6.05	1.4
DRC-CES	6.75	1.01
SF-CES	6.49	1.07
TW-CES-BLK	6.49	1.39
DRC-CES-BLK	6.93	1.01
SF-CES-BLK	6.76	1.07

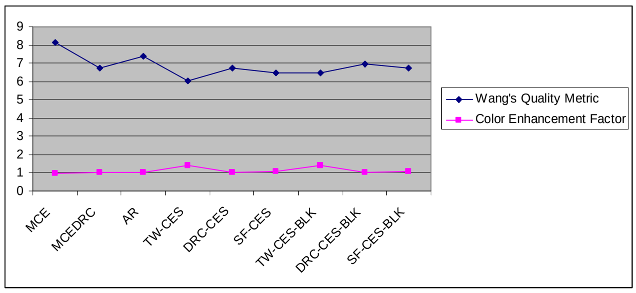

Fig. 6 Various Enhancement Techniques and Quality Metrics

Wang's quality metric comprises of sharpness and blocking estimations. Hence, it is questionable to use it solely for sharpness estimation, even though the reliability of the results is decent. Nonetheless, the results for the metric in context of sharpness estimation are displayed in Fig 5 and Table 1. The chart shows high performance while using TW-CES with Color Enhancement Factor.

5. Conclusion and Future Work

The multispectral image compression plays a key role in the success of remote sensing applications. The proposed work is a class based encoding scheme for multispectral image compression. It shows that not only the transformation but also the encoding too be adaptive. The image is first decomposed into many sub images. Then it follows transformation in both spectral and spatial domain. The KL transform uses different KLT matrices for each class. The encoding algorithm adopts two techniques based on data type classes, ie., smooth or textured region. Adaptive compression shows better results in terms of both PSNR and visual quality. The compressed image is also enhanced for better effective visualization. In future research, the noise may be removed and then the image may be considered for further enhancement.

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