IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 7 Issue 10, October 2020
ISSN (Online) 2348 – 7968 | Impact Factor (2020) – 6.72
www.ijiset.com

A Survey on Hyperspectral Image compression techniques for Satellite Images

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Abstract

Remote sensing technology works with materials, identifies and defines their properties using light, that light interacts with the materials called spectroscopy. It examines how the light behaves in the target this recognizes the material based on the spectral signature. A spectral signature identifies the spectrum of materials. Spectrum is the amount of light at different wavelengths. Spectrometer splits the incoming light into a spectrum. This reflected spectrometer is commonly used in the Hyperspectral image (HSI). HSI is used in imaging spectrometer, this is collected using the hyperspectral camera. Which measures the thousands or hundreds of thousands of spectra. That collected spectra used to form an image. Each spectrum has its information. This collected spectrum has a huge amount of information, so while transmitting this data it takes more bandwidth. So need to reduce the information. This paper can see the detail about the methods used for lossless image compression.

Keywords: *Hyperspectral image, compression techniques, transformation based techniques, prediction based techniques, band reordering, Evaluation parameters***.**

1. Introduction

The hyperspectral image contains multiple spectral information are present which represents different spectral characteristics of ground materials that can be used for territory applications, monitoring the agricultural fields, and military applications. By using remote sensing technology, this hyperspectral image captures a large spectrum with higher resolution [6]. Transmission and storage are difficult in the hyperspectral image process. To reduce the difficulties of hyperspectral image ie, a huge amount of data, it is necessary to use more efficient lossless or lossy compression techniques [6]. By using the lossless compression techniques user can preserve all the information and from the compressed data user can retrieve the original spectral data but it is difficult to achieve and satisfy the difficulties of onboard data transmission [6]. Lossy compression techniques that give more compression ratio (CR) can be considered based on applications. In this lossy compression, the user cannot achieve the original data because of distortion.

Compression of a hyperspectral image can be categorized into three are prediction-based techniques, vector quantization, and transformation techniques based on lossy and lossless **image** compression [24]. In prediction-based techniques, the predictor will predict the similarities between a neighboring pixel and spectral bands. Based on prediction-based techniques, the predictor will perform decorrelator all the original data, and the coder calculates the prediction error. The problem with this prediction based method is optimization. Lookup tables (LUT) [7, 9], and modified context-based adaptive lossless image coding (CALIC) [8, 10].are gives a better solution of prediction-based techniques. Based on Vector Quantization compression techniques codebooks are constructed, in that codebook, each vector is assigned to the codeword. Mean normalized vector quantization (M-NVQ) is used for lossless image compression. Followed this optimize spatial M-NVQ and spectral discrete cosine transform (DCT) are used for both lossy and lossless image compression to increase the compression ratio. Finally, transformation based techniques, data in the image are converted into another domain where the data are less correlated. The Karhunen–Loève transform (KLT), discrete Fourier transform (DFT), and Discrete Cosine transform (DCT) are some of the transformation techniques of hyperspectral image techniques. In these transformation based techniques, some hybrid algorithms can achieve a better compression ratio, fewer distortions, and better performances. Generally, since the correlation in the spectral dimension of hyperspectral data is usually much higher than the correlation in the spatial dimension, there is still a great challenge in compressing hyperspectral data. Therefore, to search for effective algorithms is important in hyperspectral image compression [6].

1.1 Work is done:

First, need to convert high-dimensional data into a readable form for that we need transformation. Transformation is very important in preprocessing and enhancement of image processing. Image contains noise, due to this can give rise in high-frequency components, so can use some sort of transformation [6] [24], by using this user can get the improved image coefficient by suppressing the high-frequency components. So, the modified image has some information without noise. This image transformation is very much useful in image compression. Hyperspectral images have two redundancies are spatial and spectral.to find the similarities between the pixel in a different band and pixels in the same band need to find a spectral correlation. Spectral correlation is much stronger than spatial correlation. So, need to eliminate both spatial and spectral correlation in hyperspectral images [28]. For that can use band reordering [25] methods to increase the compression performance.

2. Methodology

2.1 Transformation based techniques:

2.1.1. KL Transform:

This is transformation is different from the other transformations.in this transformation forward and inverse transformation values depend on the statistical properties of vectored representation of the data. Here initially data should be represented in vector forms A, from this need to find mean

Mean $\mu_x = E\{X\}$ ………….. (1)

Covariance $C_X = E\{(X - \mu_X)(X - \mu_X)^T\}$ ……….. (2)

Using this covariance matrix can find the set of orthogonal Eigenvector e_i of the set x, so this eigenvector can form matrix A, this formation depends on the first-row corresponding to the largest values of Eigenvalue and the last row corresponding to lowest values of covariance matrix Cx.

KL Transformed matrix of A,

$Y = A(X - \mu_X)$ …………….. (3)

At present three are three techniques of compression are transformation based techniques [6] [24], prediction-based techniques [26], and vector quantization based techniques [6]. Now we can see the transformation techniques and band reordering method in detail and all also will see some compression techniques.

2.1.2. Wavelet transform:

Wavelet transform has more advantages than Fourier transforms, wavelet transforms are functions which concentrate in time and frequency around a certain point but Fourier transforms which represents signals only in frequency.

In wavelet transform, if we apply a low pass filter on rows to the original image will get a horizontal approximation. Again if we apply LPF on columns wise to this horizontal approximation will get an approximated image (LL) and if we apply HPF column-wise to this horizontal approximation will get vertical details on the image (LH). if we apply a High pass filter(HPF) on rows to the original image will get horizontal details. Again if we apply LPF on columns wise to these horizontal details will get horizontal details (HL) and if we apply HPF on columns wise to these horizontal details will get diagonal details of the image (HH).

In a 3D transform, eight sub-band cubes are created at the first decomposition level. In that approximated coefficient which gives the most significant information represented by X wavelet coefficients with intensity l in three dimensions (x, y, z). in a low-resolution image there are high-frequency bands that contain edges. The size of high-frequency components size in DWT can further be increased with factor two and represented by Y wavelet coefficients with intensity l in three dimensions (x, y, z) are defined by

$$X_n^l\,(x,y,z) = \frac{1}{2}\left(X_{2n}^{l-1} + X_{2n+1}^{l-1}\right) \quad \text{…………………. (4)}$$

$$Y_n^l\,(x,y,z) = \frac{1}{2}\left(X_{2n}^{l-1} - X_{2n+1}^{l-1}\right) \quad \text{…………………. (5)}$$

This lowest sub-band is encoded by DPCM.

2.1.2.1 DPCM:

This shows the significant relationship between the bands. Audio and video signal has more redundancy bits. Analog signals are sampled and quantized and the prediction filter is used to predict the coefficients minimizing the error signals, so, it is used to find out the correlation between the successive bits.

2.1.3. Discrete Cosine transform (DCT):

Using this discrete cosine transformation method, the image is converted into another form i.e. if the image in the spatial domain can be transformed into the Frequency domain using DCT. This method is used to separate or divides the image or signal values based on intensity (spectral sub-bands). The main important property of DCT is the energy compaction property. Coefficients are lying in one part of the region i.e. near the origin. This property is used for data compression. 3D DCT is applied to the hyperspectral image which transforms the image in the form of Discrete Coefficients. 3D coefficients can be achieved by applying 2D DCT in pixel vectors. The 2-D DCT f (x,y) of size N x N is given as follows:

$$C(u, v) = \alpha(u) \times \alpha(v) \sum_{x,y=0}^{N} \{ f(x,y).\cos[(\frac{(2x+1)\pi u}{2\pi}).\cos[(\frac{(2y+1)\pi v}{2\pi})] \quad \ldots\ldots\ldots (6)$$

$$\text{Where } \alpha(u) = \begin{cases} \frac{\sqrt{1}}{N} & u = 0 \\ \frac{\sqrt{2}}{N} & u = 1,2,\ldots N \end{cases}$$

From this cosine matrix C (u,v) most of the energy in the signal lies in low-frequency components that are lying in the leftmost top corner of the cosine matrix and high-frequency components are lie in the rightmost bottom value of the cosine matrix. Compression can be achieved by eliminating high-frequency components which are very small and negligible.

2.2. Prediction based techniques:

2.2.1. Recurrent neural network (RNN):

RNN methods are used, its output depends on the current state of the inputs. Cyclic neural networks are used. The deep RNN structure is used to predict the next pixel by using the previous signal and data features. Prediction unit is present in the body structure of RNN that reads the current input pixel and output value. State C shifted to the next cell from the current cell. In a theoretical view of the neural network, the structure has infinite duplications. Long short-term memory (LSTM) model most widely used model in RNN. This method stating long and short-term dependencies and this is better than simple RNNs [27].

The Neural network (NN) is formed in three layers are the input layer, the hidden layer, and the fully connected layer. To predict the similarity between the spectral bands, the entire image spectral is distributed into three slices are the first Slice of spectral is the first band of the spectrum using the neighboring pixel prediction method, the second slice of the spectral is the first order of first N-1 bands using an inter-prediction algorithm (N is the prediction order), and the third slice is all the remaining band sequence in RNN [27].

2.2.2. Linear Prediction Algorithm:

This algorithm considers one of the band as a reference, the reference should be varied from the other bands. In the Worst case, these reference bands are independent of each other. So, for orthogonal reference band computation, one of the methods is KL transform but here K-means clustering algorithms are used because it gives centroid of K number cluster and each centroid of K clusters is different from each other means that variety of the bands remains the same.

The image is clustered into several clusters depends on the required features. This reflects the correlation between the bands that construct the feature vectors. If a correlation is similar that means both the bands have the same value. This paper k-means clustering band algorithm was used by using this centroid of each cluster which gives the relationship between the bands.

The bands' correlation is calculated by Eq. (7) as below:

$$r_q\,(\mathrm{p}) = \frac{\sum_{\mathrm{i,j=0}}^{\mathrm{N,M}} \left(I(i,j,p) - \overline{I(i,j,p)}\right)\left(I(i,j,q) - \overline{I(i,j,q)}\right)}{\sqrt{\sum_{\mathrm{i,j=0}}^{\mathrm{N,M}} \left(I(i,j,p) - \overline{I(i,j,p)}\right)^2 \sum_{\mathrm{i,j=0}}^{\mathrm{N,M}} \left(I(i,j,q) - \overline{I(i,j,q)}\right)^2}} \quad \ldots\ldots\ldots (7)$$

Where i, j are the pixels in p and q bands. i bar and j bar are the means of the band p and q. band q is the reference band, so correlations between the band Q and others are feature vectors which represented by

$$vec_q = \{r_q(1), r_q(2), \ldots\, r_q(p) \ldots.\, r_q(P)\}, p = 1,2, \ldots P \quad \ldots\ldots (8)$$

By using this Matrix r formed by using K –clustering algorithm. Here hyperspectral image divided into k clusters k values are fixed. Each centroid clusters calculated regarding ref_k is obtained by Eq. (3):

$$ref_k = \sum_{n-1}^{c(k)} I^k\,(i,j,n)/c(k) \quad \ldots.. (9)$$

Where K is the cluster and C (k) number of bands in the cluster k.
This K value is important to calculate the Bit error (BR) and signal to noise ratio (SNR). If k value increases, then BR and SNR increases.

2.3 Band reordering methods:

The natural order of hyperspectral image can be reordered based deterministic, probabilistic, and predictor related. Similarity measure can be determined by using Correlation Coefficient, Euclidian Distance, Maximum Absolute Distance, etc [25]. The probability of similarities is measured based on information measures such as mutual information, conditional entropy, and binary coding or Markovian measure [25]. Finally, the predictor related similarity measure techniques are based on Residual bands [25].

2.3.1. Band reordering based on consecutive continuity breakdown heuristics (BRCCBH).

First HSI can be represented by the Correlation matrix formed based on the maximum weighted tree (MWT) and order based on their weights. Based on the highest coefficient value Comparing current coefficient value with consecutive values, if greater than or equal to this value then must perform continuity breakdown. Example threshold value must set and compare the consecutive bands if those bands are higher than or equal then that value considers as 1 from those bands one group. If it's less than or equal that values are represented by 0 and from those bands are one group. So like these similarity bands are formed.

2.3.2. Band reordering based on weighted-correlation heuristics (BRWCH)

In the band reordering method weight is assigned to the current bands and this will be helpful when finding the next band of this order [25]. To construct the reordered list this algorithm calculates the maximum weighted value of the current correlated band and it takes two or three previous bands [25]. The band reordering performed in two ways, either from the initial band or from the highest pair of correlated bands in the data cube. Finally, in both cases, the highest weighted correlated band is selected for constructing the reordered list.

2.3.3. Band reordering based on the segmentation of bands (BRSB)

The spectral image is collected from the satellite which contains a large number of spectral bands and based on the average correlation value these spectral bands are spilled into several segments, this will be helpful for further processing the data [25]. To achieve better classification and color display the band segmentations are used. [25].

3. Evaluation parameters:

$$\text{Compression ratio} = \frac{\text{original image size in bits}}{\text{compressed bit stream in bits}} \tag{10}$$

$$\text{Bit rate (BR)} = \frac{\text{number of bit pixel in original image}}{\text{compression ratio}} \tag{11}$$

$$\text{PSNR} = 10\, log_{10} \frac{maximum\ possible\ pixel\ values\ of\ the\ image}{Mean\ square\ error} \tag{12}$$

$$\text{Mean Square Error (MSE)} = \frac{Cumulative\ squared\ error\ of\ compressed\ image}{original\ image} \tag{13}$$

4. Conclusions

In this paper, various hyperspectral image compression techniques are proposed. Possible way of lossless hyperspectral image compression techniques are transformation based techniques prediction-based techniques and vector quantization based technique and band reordering method are presented. In these techniques various algorithms are described and By using these algorithms can achieve better image compression. Though multiple techniques are available, need for some improvement in image compression techniques in terms of compression ratio, bit rate, PSNR, and mean square error.

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