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A Novel Approach for Hyperspectral Lossless Image Compression

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Abstract:

Image compression of Hyperspectral data is necessary because of the large storage requirements. The algorithms developed in this paper are compared in terms of compression performance and computational complexity against the best existent algorithms. The algorithms are Kalman Spectral Prediction (KSP) algorithm and Low Complexity Lossless Compression for Image (LOCO-I) algorithm. In this KSP is a Band Sequential (BSQ) format and LOCO-I is a Band Interleaved by Line (BIL) format. The band sequential format requires that all data for a single band covering the entire scene be written as one file. In band interleaved by line format, the data for the bands are written line by line onto the same tape. Many researches like this format because it is not necessary to read serially past unwanted information if certain bands are of no value. It is useful format if all the bands are to be used in the analysis. If some bands are not of interest, the format is inefficient. In this we compare the two different formats of data. LOCO-I uses the information of only one previous band for prediction stage. However, the KSP algorithm alternates the information of more than one previous band for prediction. In this KSP algorithm performs greater compression ratio than LOCO algorithm because KSP algorithm uses more than one band for the prediction. In this LOCO algorithm compress the input data half of its size but KSP algorithm compress the data more than half of its size. The time complexity of KSP algorithm is less compared to LOCO algorithm. The compression ratio for the KSP algorithm is 61% but the compression ratio for LOCO algorithm is 55%. KSP algorithm is more efficient because it gives the spectral characteristics of the data using the interband prediction.

Keywords—**Hyperspectral image, Image compression, prediction, KSP, LOCO, compression ratio.**

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I. INTRODUCTION

Hyperspectral images are widely used in a number of civilian and military applications. The Hyperion imager carried on the EO-1 (Earth Observing-1) satellite is also a common source of hyperspectral data. Image compression is particularly important for this application, where the images must be compressed and sent over a limited bandwidth carrier before analysis can take place. The Hyperion sensor consists of 242 spectral bands, where each pixel has 12 bits of precision. The images obtained from a Hyperion sensor can have a size of up to approximately 550Mbytes.

Image compression is a very important problem in the image-processing field since very large images require a large amount of storage space [1]. One example of very large image is those taken with hyperspectral sensors. Hyperspectral images can be defined as images with a high spectral resolution, typically 100 to 300 different wavelengths. A digital image can be represented as an array of matrices, in which each element of the matrix is known as a pixel [2], [3].

The lossless compression algorithm is necessary in cases where the exact image data must be recovered. Lossless compression is archived by the transformation and codification of the data using fewer bits to represent the data. Hyperspectral images can be modeled as a 3-dimensional matrix composed of spatial and spectral coordinate. Lossless compression algorithms are typically divided into two stages, a prediction stage to eliminate redundancy and a coding stage. The data actually stored in a compression algorithm is the coded difference between the original data and the predicted value and is called prediction error [5], [6]. If the code, the prediction error and the prediction method used are known, the original data can be recovered. To represent an image signal with the smallest possible number of bits without loss of any information, thereby speeding up transmission and minimizing storage requirements.

Hyperspectral image has high spatial and spectral correlations, its enormous data volume brings about problems in data storage, transmission and processing, So we need a method to reduce the storage capacity of the data. To increase the processing speed and to minimize the error between originality and decompressed image, Hyperspectral image compression is needed. No image data are lost during lossless compression. Many unknown image background signatures and noise also preserved during lossless image compression

II. STUDY AREA AND DATA DESCRIPTION

The Hyperion sensor consists of 242 spectral bands, where each pixel has 12 bits of precision with the wavelength of 400 to 2400nm. The images obtained from a Hyperion sensor can have a size of up to approximately 550Mbytes.The Hyperion sensor onboard NASA's Earth Observing 1 satellite is the first space borne hyperspectral instrument to acquire both visible/near-infrared (400- 1000 nm) and shortwave infrared (900-2500 nm) spectral data. Hyperion is a push broom imager with spectral range of 0.4 to 2.4 µm and spatial resolution of 30m. It has spectral resolution of 10nm and swath width of 7.6 km.

Fig.1 Hyperion image

The study area chosen for the present study is Tirunelveli District in Tamilnadu, India. The area falls within 8°59' and 09°0' of Northern latitude and 77°5' and 77°6' of Eastern longitude of Tirunelveli District.

The software used in this study is MATLAB 7.8.0 (R2009a). The MATLAB is a high-performance language for technical computation, visualization and programming. It is easy-to-use environment.

III. METHODOLOGY

Compression is the process of reduction in size of data in order to save space or transmission time. Image compression is the process of minimizing the size of data without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. Lossless compression is a compression technique that does not lose any data in the compression process [9], [10]. Hyperspectral image has high spatial and spectral correlations, its enormous data volume brings about problems in data storage, transmission and processing, so we need a method to reduce the storage capacity of the data. The methodology workflow is shown in Fig.2.

The hyperspectral lossless image compression algorithms described as are

1) LOCO algorithm
2) KSP algorithm

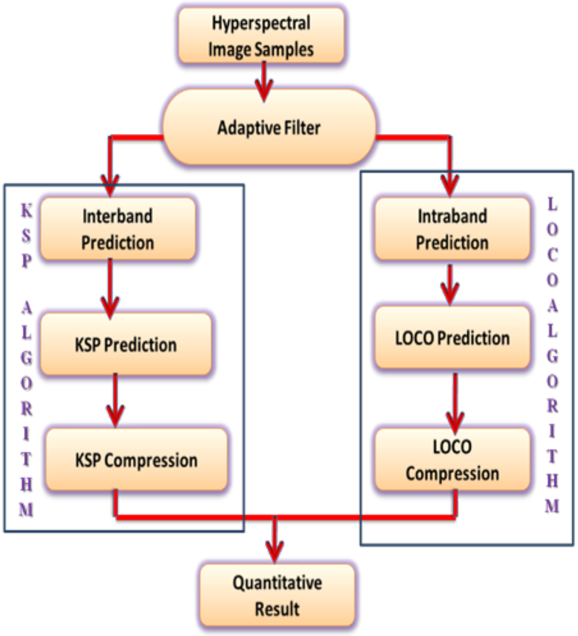

Fig.2 Methodology workflow

A. Adaptive Filter

An adaptive filter is a filter that self-adjusts its transfer function according to an optimizing algorithm. Because of the complexity of the optimizing algorithms, most adaptive filters are digital filters that perform processing and adapt their performance based on the input. The adapting process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify the filter coefficients to minimize the cost on the next iteration.

Overview of Adaptive Filters and their applications are

1) System Identification— Using adaptive filters to identify the response of an unknown system.
2) Inverse System Identification—Using adaptive filters to develop a filter that has a response that is the inverse of an unknown system.
3) Noise or Interference Cancellation—performing active noise cancellation where the filter adapts in real-time to remove noise by keeping the error small.
4) Prediction— describes using adaptive filters to predict a future values.

B. Intraband Prediction

Intraband prediction is applied only to the first image along the spectral line. The median predictor defined in LOCO was employed here due to its simplicity and efficiency for still images. Let y be the current pixel and NW (northwest), N (north), and W (west) denote three neighboring pixels, respectively. The intraband estimate of pixel y

$$y = \begin{cases} \min(N, W), & \text{if } NW \geq \max(N, W) \\ \max(N, W), & \text{if } NW \leq \min(N, W) \\ N + W - NW, & \text{otherwise} \end{cases} \quad (1)$$

C. Interband Prediction

For interband prediction, a third-order predictor is adopted and has the following prediction formula:

$$y = \alpha(v - m_v) + \beta(w - m_w) + \gamma(x - m_x) + m_y \quad (2)$$

Where "*x*," "*w*," and "*v*" denote the pixels collocated with the current pixel in three previous bands and "*m*" stands for the expectation value of a random variable. Prediction coefficients *α*, *β*, and *γ* can be derived by solving a Wiener–Hopf equation

$$\begin{bmatrix} \sigma_v^2 & \sigma_{wv} & \sigma_{xv} \\ \sigma_{wv} & \sigma_w^2 & \sigma_{xw} \\ \sigma_{xv} & \sigma_{xw} & \sigma_x^2 \end{bmatrix} \begin{matrix} \alpha \\ \beta \\ \gamma \end{matrix} = \begin{matrix} \sigma_{yv} \\ \sigma_{yw} \\ \sigma_{yx} \end{matrix} \quad (3)$$

The statistical parameters can be approximated as.

$$\begin{aligned} \sigma_x^2 &= E\{x^2\} - m_x^2 \\ &= \frac{1}{M^2}\left(M \textstyle\sum_{i=1}^{M} x_i^2 - \left(\sum_{i=1}^{M} x_i^2\right)\right) \end{aligned} \quad (4)$$

$$\begin{aligned} \sigma_{wy} &= E\{wy\} - m_w m_y \\ &= \frac{1}{M^2}\left(M \textstyle\sum_{i=1}^{M} w_i y_i - \left(\sum_{i=1}^{M} w_i\right)\left(\sum_{i=1}^{M} y_i\right)\right) \end{aligned} \quad (5)$$

D. LOCO-I Prediction

This algorithm is a lossless compression algorithm for continuous-tone images, which combines the simplicity of Huffman coding with the compression potential of context models. The LOCO-I algorithm uses the information of three neighboring pixels (the pixels $y1$, $y2$ and $y3$ in fig.4.2) in the same spectral band in order to do the prediction, in other words it only uses the spatial information. This algorithm consists of a performance test to detect vertical and horizontal edges. If an edge is not detected, then the predicted value is y1+y2-y3, as this would be the value of y, if the current pixel belonged to the plane defined by the three neighboring pixels. The LOCO-I predictor is defined as:

$$y = \begin{cases} \min(y1, y2), & \text{if } y3 \geq \max(y1, y2) \\ \max(y1, y2), & \text{if } y3 \leq \max(y1, y2) \\ y1 + y2 - y3, & \text{otherwise} \end{cases} \quad (6)$$

As mentioned above, this predictor detects the existence of an edge. For example, if a vertical edge exists then typically y1<=y2, and the predictor in many cases chooses the pixel y1 for prediction. If a horizontal edge is detected the predictor selects the pixel y2. However, if any edge is detected the predictor uses the plane y1+y2-y3for prediction.

E. LOCO-I Compression

The principle of context adaptive coding is to attempt to model the conditional entropy of symbols based on their surrounding neighborhood. This can be seen as a generalized form of prediction where each context determines a complete probability model for the new data (as opposed to only a predicted value, which would be the mean of the conditional distribution). The number of different values for the neighborhood can be quite large, especially for a large alphabet sources, and thus it is normal practice to partition the possible neighborhoods into a smaller set of classes. The appropriate number of classes has to be kept small based on complexity consideration but also to avoid "context dilution" situations [9].

The total number of parameters in a model depends on the number of free parameters defining the coding distribution in each context and in the number of contexts. The algorithm LOCO-I uses a piecewise- linear predictor with rudimentary edge detecting capability, and is based on a very simple context model, determined by quantified gradients, "thus capturing the level of activity (smoothness, edginess) surrounding a sample, which governs the statistical behavior of the prediction errors". These gradients are defined by the following differences:g1=y4-y3,g2=y3-y2,g3=y2-y1, and g4=y1-y5 (See fig. 4.2) By symmetry,g1, g2and g3 influence the model in the same way and is quantified into up to 9 connected regions by a quantifier k, where the value k yield the shortest code length. These gradients are used to find the values of the boundaries between quantization regions. Those regions are represented by an alphabet of 16-bit per pixel, and they determine the contexts. This is achieved through a single parameter probability distribution per context, efficiently implemented by an adaptive, symbol-wise, Golomb-Rice code. In addition, reduced redundancy is achieved by embedding an alphabet extension in regions. "LOCO-I have achieved the best compromise between compression performance and computational complexity".

F. KSP Prediction

The KSP predictor is based on the following linear model:

$$X_{j(x,y)} = \alpha X_{j-1}(x, y) + \beta \quad (7)$$

Where α and β minimize the prediction error. The Kalman filter is employed to estimate the non-measurable components of the state xj€R with set of real numbers, of a discrete-time random process described by the following linear stochastic difference equation:

$$X_j = Ax_{j-1} + u_j + w_{j-1} \quad (8)$$

The prediction Xj(x, y) is obtained through the Kalman filter equation

$$X_j(x, y) = X_{j-1}(x, y) + K_j(x, y)[z_j(x, y) - X_{j-1}(x, y)] \quad (9)$$

G. KSP Compression

KSP algorithm uses more than one previous band in the predictor stage. The data are smoothed by Kalman filter. Kalman filter predict the stages of the dynamic systems from a series of noisy environment. It gives the spectral information clearly by using interband prediction. KSP algorithm has better performance on raw data [10]. The coefficient $\alpha j(x, y)$, which models the correlation between a pixel in band j and the co located pixel in band $j - 1$, is taken as

$$\alpha_j(x, y) = \frac{X_j(x-1, y) + X_j(x, y-1)}{X_{j-1}(x-1, y) + X_{j-1}(x, y-1)} \tag{10}$$

For the KSP algorithm, we employ the same context-based entropy coding stage and it is based on arithmetic coding. The only difference lies in the Threshold setting for context selection; the thresholds are set to q1 = 12, q2 = 20, and q3 = 40 to accommodate 16-bit data.

H. Quantitative Analysis

In this quantitative analysis we compare the compression ratio of the LOCO algorithm and KSP algorithm. In order to get the spectral characteristics of the data, interband prediction technique is used. By using this interband prediction technique we can compute the KSP compression. For spatial characteristics of the data, intraband prediction technique is used. LOCO compression [7].

In this quantitative analysis we compare the compression ratio of the LOCO algorithm and KSP algorithm. In order to get the spectral characteristics of the data, interband prediction technique is used. By using this interband prediction technique we can compute the KSP compression [8].

For spatial characteristics of the data, intraband prediction technique is used. LOCO compression can be performed by using the intraband prediction technique. In LOCO algorithm the prediction stage can be done by means of only one previous band .But in KSP algorithm more than one previous band can be taken for the prediction stage. The compression ratio is compared with the LOCO and KSP algorithm.

IV. RESULTS

The Hyperion image of dimension 600*600 has been given as input to the preprocessing. The adaptive filter is used to remove the noise and it is used to convert an intensity image to a binary image. In order to get the spectral characteristics of the data, interband prediction technique is used. By using this interband prediction technique we can find the KSP compression.

For spatial characteristics of the data, intraband prediction technique is used. LOCO compression can be performed by using the intraband prediction technique. The compression ratio is compared with the LOCO and KSP algorithm. The computational time is also compared with the LOCO and KSP algorithm. The whole process is implemented in Matlab environment.

A. Adaptive Filter

The input image is given to the adaptive filter for preprocessing. The adaptive filter is used to remove the unwanted noise and the error. It is also used to convert an intensity image to a binary image. The following fig.3 shows the filtered image of the corresponding input image.

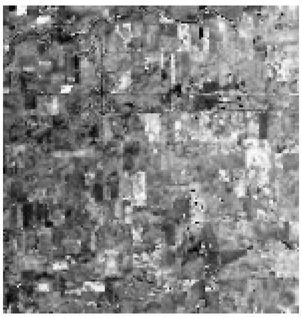

Fig. 3 Adaptive filter

B. Interband Prediction

The filtered image is given for interband prediction. The KSP compression algorithm involves the interband prediction for predicting the spectral characteristics. In this the spectral characteristics of the data are viewed clearly. This interband predicted image is given to the KSP prediction. The following fig.4 shows the interband predicted image for the corresponding filtered image.

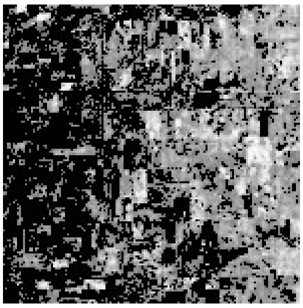

Fig. 4 Interband Prediction

C. Intraband Prediction

The filtered image is given for intraband prediction. The LOCO compression algorithm involves the intraband prediction for predicting the spatial characteristics. In this the spatial characteristics of the data are viewed clearly. This intraband predicted image is given to the LOCO prediction. The following fig.5 shows the intraband predicted image for the corresponding filtered image.

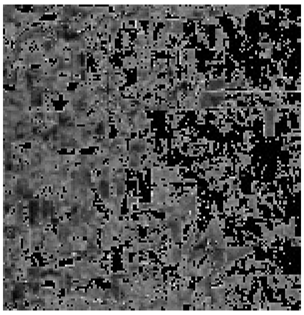

Fig. 5 Intraband prediction

D. LOCO Compression

The LOCO predicted image is given to the input for the LOCO compression algorithm. In this the LOCO predicted image is compressed using the LOCO compression. The following fig. 6 depicts the LOCO compressed image.

Fig. 6 LOCO Compression

E. KSP Compression

The KSP predicted image is given to the input for the KSP compression algorithm. In this the KSP predicted image is compressed using the KSP compression. The following fig. 7 depicts the KSP compressed image.

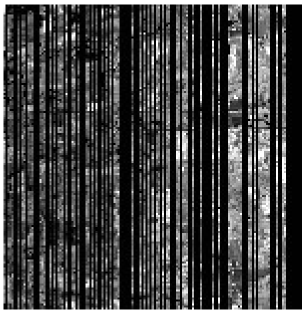

Fig.7 KSP Compression

F. Analysis

In this analysis part, the size of the image using LOCO algorithm and KSP algorithm is shown in fig.8. This histogram gives the input image, filtered image, LOCO compression and KSP compression. In this KSP and LOCO compression, x-axis represents the compression ratio and y-axis represents the number of pixels. The compression ratio of the KSP algorithm is less when compared to LOCO algorithm.

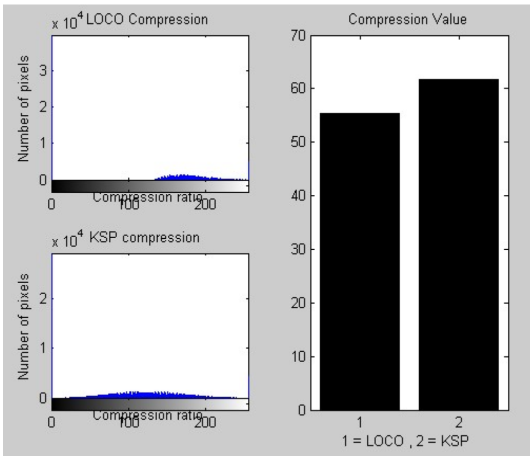

Fig.8 Compression ratio

The following fig.8 depicts the compression ratio for the LOCO algorithm and KSP algorithm. The following bar chart shows the compression ratio of the LOCO and KSP algorithm. The compression ratio for the LOCO algorithm is 55% and the KSP algorithm is 61%. In this bar chart, x-axis represents the LOCO and KSP algorithm and the y-axis represents the compression ratio.

V. DISCUSSION

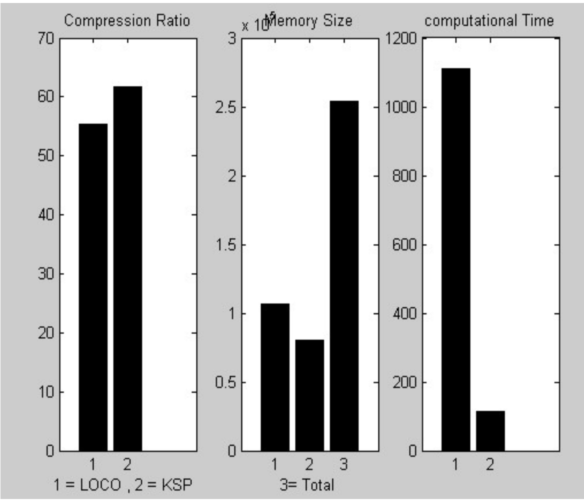

Fig.9 Analysis

The above figure 9 depicts the compression ratio, Memory size and the computational time for the LOCO and KSP algorithm. In this bar chart x-axis represents the LOCO algorithm, KSP algorithm and total amount of data. Y-axis represents the compression ratio, size of the image and the computational time in seconds for the corresponding algorithm respectively. From this bar chart, we can conclude that the KSP algorithm is best, because of compression ratio, image size and computational time.

VI. CONCLUSION

In this attempt, a novel approach for hyperspectral lossless image compression has been implemented and the performance of LOCO and KSP algorithm has been evaluated. From this two different data format, Band sequential format is good. The band sequential format requires that all data for a single band covering the entire scene be written as one file. Many researches like this format because it is not necessary to read serially past unwanted information if certain bands are of no value. In band interleaved by line format, the data for the bands are written line by line onto the same tape. It is useful format if all the bands are to be used in the analysis. If some bands are not of interest, the format is inefficient if the data are on tape, since it is necessary to read serially past unwanted data.

In this paper we selected mineral bands (185-224) for the input data. In this KSP algorithm performs greater compression ratio than the LOCO algorithm because KSP algorithm uses more than one band for the prediction. In this LOCO algorithm compress the input data half of its size but KSP algorithm compress the data more than half of its size. The time complexity of KSP algorithm is less compared to LOCO algorithm. The compression ratio for the KSP algorithm is 61% but the compression ratio for LOCO algorithm is 55%. KSP algorithm is more efficient because it gives the spectral characteristics of the data using the interband prediction.

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