行政院國家科學委員會專題研究計畫成果報告

適應性KLT壓縮技術於遙測衛星影像應用之研究

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中文摘要

本計畫針對多頻帶之遙測衛星影像,提出一高效率之適應性KLT壓縮技術o此壓縮技術充份利用衛星影像在頻帶間及空間資料之關聯性o依據衛星影像之區域特性,決定適當的影像區間,再針對各區間影像進行其對應之KL轉換o此外,此適應性KLT壓縮技術可以硬體實現其特徵值及特徵分量之調整o電腦模擬驗證此適應性KLT壓縮技術具有極佳之壓縮效能o

ABSTRACT In the study, we propose an efficient adaptive KLT algorithm for multispectral image compression to fully exploit the spectral and spatial correlation in the data. To adopt to the local terrain characteristics of multispectral image, the adaptive KLT algorithm can divide the original image into some proper regions, and transform each region image data set by the corresponding transformation function. Furthermore, the algorithm is suitable for hardware implementation. Simulation results show that the performance of the proposed adaptive KLT algorithm is better than those of the existing algorithms.

1 Introduction

Building digital libraries has become white hot in this era of internet and the World Wide Web. A digital library for geographically referenced materials can include maps, satellite images, digitized aerial photographs, and their associated metadata. Concerning satellite images, which have higher spatial resolution in wider coverage areas, and a number of spectral bands [1], their accessibility is hindered by the size of images and communication bandwidth. To alleviate these limitations, the image data should be compressed.

Since satellite images reveal high degree of spectral and spatial correlations, it must be properly exploited in the design of any multispectral compression scheme. Although there are various compression methods for spatial decorrelation [2], relatively few studies [3] for spectral decorrelation across bands have been presented. In [3], Karhunen-Loeve transform (KLT), which is theoretically the optimum method to spectrally decorrelate the image data, has been proposed to operate on the associated cross-covariance matrix of a whole image. Moreover, a typical satellite image set exhibits a number of different terrains, such as forest, desert, water and cloud. Thus, to have good compactness of spectral information, the spectral decorrelation transform must adapt to the local terrain characteristics.

In our studies, we propose an adaptive algorithm to continuously adjust eigenvalues and eigenvectors when input image data is received sequentially. Monitoring the updated eigenvalues and eigenvectors, we can determine a proper region size for each local terrain characteristics (e.g. water, forest and desert). Then, a KLT transform is adopted for each extracted terrain region in order to achieve the highest compactness of spectral information. However, the adaptive KLT algorithm is suitable for hardware implementation of multispectral image compression. Simulation results validates the better performance of the proposed algorithm.

2 Adaptive KLT Algorithm

In this section, we first review the KLT transformation, and then introduce a fixed region KLT (FR-KLT) method to improve the compression ratio. Finally, an efficient adaptive KLT algorithm is proposed, which can determine a proper region for each local terrain characteristics of image.

2.1 Karhunen-Loeve Transformation

Consider a multispectral image with s bands. The image data vector can be expressed as

$$X = [x_1, x_2, ..., x_{s-1}, x_s]^T \tag{1}$$

where x_i is the i-th band data and $'T'$ denotes the transpose. The pixel-to-pixel correlation is the form of spatial redundancy that is most often exploited by signal band image compression. Similarly, the band-to-band correlation matrix can be exploited to remove the inherent spectral correlation in multispectral image. The band-to-band covariance matrix is defined as

$$C_x = E(X - m_x)(X - m_x)^T \tag{2}$$

where $m_x = E[X]$, is the mean vector and $'E'$ denotes the expectation. Since C_x is symmetric and positive semidefinite, the eigenvalues λ_i and the eigenvectors e_i of C_x, which satisfy

$$C_x e_i = \lambda_i e_i, \tag{3}$$

have the following properties:

(1) The eigenvalues in descending order satisfy $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_s \geq 0$

(2) The matrix Φ, formed by the eigenvectors $\Phi = [e_1, e_2, ..., e_s]$ is an orthogonal matrix, that is $\Phi\Phi^T = I_s$, where I_s is an identity matrix.

The basis functions of KLT transformation are the eigenvectors of the covariance matrix C_x. The original spectrally correlated image X can be decorrelated by the KL transformation matrix Φ, and get an eigen image Y, that is

$$Y = \Phi^T X = [y_1, y_2, ..., y_s]^T \qquad (4)$$

where $y_1, y_2, ..., y_s$ are decorrelated, since the covariance matrix of Y is

$$\begin{aligned} C_y &= E[Y - E(Y)][Y - E(Y)]^T = \Phi^T C_x \Phi \\ &= Diag(\lambda_1, \lambda_2, ..., \lambda_s) \end{aligned} \qquad (5)$$

In (5), C_y is a diagonal matrix, that is, each vector of the spectrally correlated components from identical location in each band is multiplied by the KLT transformation matrix to form an output vector of spectrally decorrelated eigen components.

However, recovering the original image can be performed by inverse KLT,

$$X = (\Phi^T)^{-1} Y = \Phi Y \qquad (6)$$

2.2 Fixed-Region KLT (FR-KLT)

As discussed in the previous subsection, the KLT is theoretically the optimum method to spectrally decorrelated a set of multispectral image. But, the KLT performed in practical image transformation is non-adaptive. That is, the parameters of transformation, the KLT basis functions, are fixed for entire image set. However, a typical multispectral image set obtained from satellite exhibits a number of different terrain, such as forest, water, dessert and water. Each terrain has unique spectral signature. Thus, to achieve the highest compactness of spectral information, the spectral transformation parameters must adopt to local terrain characteristics.

In this subsection, to update the spectral transformation frequently, we introduce the Fixed-Region KLT (FR-KLT) method. In FR-KLT, we divide the whole image into several regions with fixed region size, such as 128x128, 64x64 or 32x32, respectively. Each region image set are transformed by its corresponding spectral transformation basis functions which are computed from the covariance matrix associated with each region image set. The images in each region are spectrally decorrelated via KLT and produce the eigen images. To further exploit the spatial correlation between the eigen image data, the resulting spectrally decorrelated eigen images are then spatially decorrelated by using the JPEG standard [5].

The FR-KLT consists of four modules: (1) Data partition, (2) KL transformation, (3) Mapping eigen image into 8-bit eigen image, (4) JPEG compression of eigen image. In data partition module, the multispectral image set are partition into several non-overlapping image region sets, which are sequentially fed to the KL transformation module for spectrally decorrelation. In the KL transformation module, the region set is spectrally decorrelated to produce a set of eigen image. In the module of mapping eigen image into 8-bit eigen image, the eigen image set via linear/nonlinear mapping of each eigen image into 0-255 range. Then, the spectrally decorrelated 8-bit eigen image sets are compressed by the next JPEG module.

The FR-KLT approach entails transmission and processing some overhead information, which includes the correlation matrix and eigen image quantization parameters for each region. For a image with s bands, and the region size selected to be rxr, the overhead bit rate is approximately equal to $\frac{8(s+1)(s+2)}{sr^2}$. Thus, the smaller the region size, the more efficient is the spectrally decorrelation process. But, the drawback with the selection of small region size is resulting increase in the overhead bit rate due to an increase in the number of regions.

2.3 Adaptive Variable Region KLT (AVR-KLT)

As discussed in section 2.2, the FR-KLT approach will improve the compression ratio. But, in FR-KLT the image partition is image independent. To determine a proper region size for each local terrain characteristics, the KL transformation parameters must be continuously updated according to the image spectral characteristics.

In this subsection, we present an adaptive KLT algorithm, which can continuously adjust eigenvalues and eigenvectors when input image date is received sequentially. Since the eigencomponents reveals the information contents of spectral characteristics, monitoring the updated eigenvalues and eigenvectors, we can determine a proper region size for each local terrain characteristics. Then, a proper KLT transformation is adopted for each extracted terrain region.

For a sequentially input image data X, we use an adaptive algorithm [4] to adjust the eigenvalues and eigenvectors by using the previously determined eigenvalue $\lambda_i(l)$ and eigenvector $e_i(l)$ of the adjacent region l. At first, we orthogonalize the input data

$$\begin{aligned} X_1 &= X \\ X_i &= X_{i-1} - e_{i-1}^H(l) X_{i-1} e_{i-1}(l) \quad i = 2, ..., s \end{aligned} \qquad (7)$$

The eigenvalues are adjusted by

$$\lambda_i'(l) = (1-\alpha)\lambda_i(l) + \alpha |e_i^H(l) X_i|^2 \qquad (8)$$

The eigenvalues are adjusted and normalized by

$$e_i'(l) = e_i(l) + \frac{\alpha}{(1-\alpha)\lambda_i(l)} X_i^H e_i(l) X_i \qquad (9)$$

and

$$e_i'(l) = \frac{e_i'(l)}{\| e_i'(l) \|} \qquad (10)$$

where α is the forgetting factor. Concern the adjacent image data should have a similar local terrain characteristics, and the eigencomponents correspond to the information contents of spectral characteristics. Thus, monitoring the updated eigenvalues and eigenvectors, we can determine the combination of adjacent region with the sequential image data by the decision function

$$F = A * \frac{\left|\frac{\lambda_{max}(l)}{\lambda_{min}(l)} - \frac{\lambda'_{max}(l)}{\lambda'_{min}(l)}\right|}{\frac{\lambda_{max}(l)}{\lambda_{min}(l)}} + B * \frac{\| \Phi(l) - \Phi'(l) \|}{\| \Phi(l) \|}, \tag{11}$$

where A and B are the weighting factor, $0 \leq A, B \leq 1$, $\Phi(l) = [e_1(l), ..., e_s(l)]$, and $\Phi'(l) = [e'_1(l), ..., e'_s(l)]$ If the decision function $F \leq \zeta$, where ζ is the threshold, the input sequential image data X combines with the adjacent region l and set $e_i(l) = e'_i(l)$ and $\lambda_i(l) = \lambda'_i(l)$; otherwise, create a new region for the sequential image data X. The above adaptive KLT algorithm may determine a proper region for each local terrain characteristics in pixel based. However, to reduce the transmission overhead bit rate, the proposed algorithm may be modified in block based. We may divide the image into some small blocks with fixed block size, such as 2x2, 4x4, or 8x8. The eigencomponents are adjusted according the sequential block data. Then, we may determine the combination of the adjacent region with the block image data.

The AVR-KLT algorithm is summarized as follows

1. Select the region number P and threshold ζ.
2. Orthogonalize the sequential input image data
   $X_1 = X$
   $X_i = X_{i-1} - e^H_{i-1}(l)X_{i-1}e_{i-1}(l) \quad i = 2, ..., s$
3. Adjust the eigenvalue λ_i and eigenvector e_i by the previously determined eigenvalue $\lambda_i(l)$ and eigenvector $e_i(l)$ of adjacent region l
   $\lambda'_i(l) = (1-\alpha)\lambda_i(l) + \alpha|e^H_i(l)X|^2$
   $e'_i(l) = e_i(l) + \frac{\alpha}{(1-\alpha)\lambda_i(l)} X^H e_i(l)X, i = 1, ..., s$
4. Determine the combination of region l with the image data X by the criterion
   $$F = A * \frac{\left|\frac{\lambda_{max}(l)}{\lambda_{min}(l)} - \frac{\lambda'_{max}(l)}{\lambda'_{min}(l)}\right|}{\frac{\lambda_{max}(l)}{\lambda_{min}(l)}} + B * \frac{\|\phi(l) - \phi'(l)\|}{\|\phi(l)\|} \leq \zeta$$
   and set $e_i(l) = e'_i(l)$, $\lambda_i(l) = \lambda'_i(l)$. Otherwise, create a new region for image X.
5. Repeat 2. and 4. until the whole image has divided into P regions.

After the image has been divided into proper regions according the local terrain characteristics, the corresponding KLT transformation is performed for each region and produce a resulting spectrally decorrelated eigen image. Then the eigen images are further compressed via JPEG standard. Furthermore, the eigencomponents updated in equations (7) to (9) may be implemented in one parallel structure [6]. Thus, The AVR-KLT algorithm is suitable for hardware implementation.

3 Simulations

We have conducted the experiments on the Systeme Probatoire d'Observation de la Terre (SPOT) satellite images, which have G, R, and IR bands coded at 8 bit/band, and on LANDSAT satellite images which have 7 bands coded at 8 bit/band. The image size is 512x512. The test images "Harbour-I" and "Harbour-II" are SPOT satellite images and the image "Harbour-III" is Landsat satellite image. The test images are spectrally decorrelated by the proposed algorithm to produce eigen images. The resulting eigen images are then spatially decorrelated by using the JPEG standard [5] with Q-factor being 50. In simulations, we compare the performance of various multispectral compression algorithms: JPEG standard[5], KLT-JPEG [3], the proposed FR-KLT and AVR-KLT. The test images "Harbour-I" and "Harbour-II" are divided into 8 different terrain regions, and image "Harbour-III" are divided into 4 regions, respectively, for the proposed FR-KLT and AVR-KLT algorithms. Table 1 shows the compression ratio(CR) and average peak signal-to-noise ratio(APSNR) for various multispectral compression algorithms. The experimental results in Table 1 show that the proposed AVR-KLT compression scheme can improve compression ratio about 40 percent as compared with KLT-JPEG method when APSNR difference between two compression schemes are less than 2 dB. Furthermore, the CR value of the proposed AVR-KLT is better than that of the FR-KLT method with about 1 dB degradation of APSNR. Finally, to illustrate the output picture quality of the proposed scheme, we display original and recompressed image of the proposed AVR-KLT scheme in Fig. 2, 3 and 4, respectively, for three test Harbour images.

4 Conclusions

In the study, we have proposed an adaptive compression algorithm AVR-KLT for multispectral image compression. The proposed AVR-KLT algorithm can determine a proper region for different local terrain characteristics of image, and a corresponding KLT transformation is adopted for each extracted terrain region. Furthermore, the proposed algorithm is efficient and suitable for hardware implementation. Simulation results show that the proposed AVR-KLT can improve the compression ration about 40 percent than those of the existing algorithms with acceptable degradation of image quality.

Image		JPEG	KLT-JPEG	FR-KLT	AVR-KLT
Harbour-I	CR	14.86:1	21.57:1	25.13:1	29.74:1
	APSNR	33.54	33.22	32.91	31.60
Harbour-II	CR	14.01	21.71:1	25.66:1	26.82:1
	APSNR	32.41	33.10	32.40	31.68
Harbour-III	CR	9.89:1	26.63:1	31.19:1	33.63:1
	APSNR	28.29	26.74	26.90	25.80

Table 1: Performance comparison of various multispectral compression algorithms.

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(a)

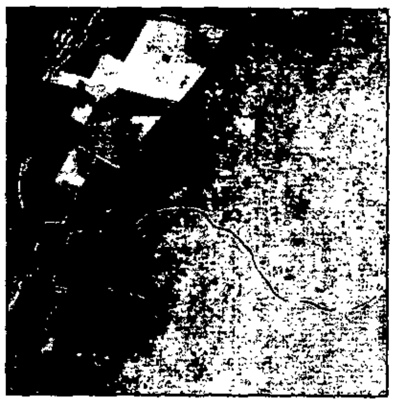
(b)

Figure 1: "Harbour-I" image: (a)original image (b)decompressed AVR-KLT image

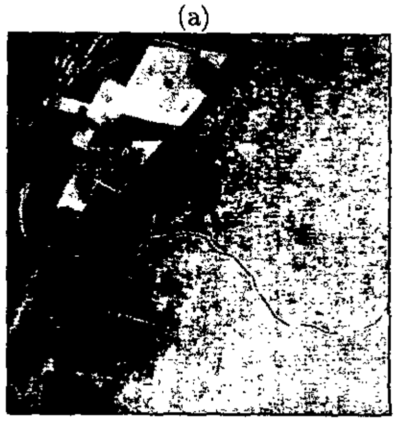
(a)

(b)

Figure 2: "Harbour-II" image: (a)original image (b)decompressed AVR-KLT image



(a)



(b)

Figure 3: "Harbour-III" image: (a)original image (b)decompressed AVR-KLT image