A Linear Mixture Analysis-Based Compression for Hyperspectal Image Analysis

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ABSTRACT

In this paper, we present a fully constrained least squares linear spectral mixture analysis-based compression technique for hyperspectral image analysis, particularly, target detection and classification. Unlike most compression techniques that directly deal with image gray levels, the proposed compression approach generates the abundance fractional images of potential targets present in an image scene and then encodes these fractional images so as to achieve data compression. Since the vital information used for image analysis is generally preserved and retained in the abundance fractional images, the loss of information may have very little impact on image analysis. In some occasions, it even improves analysis performance. Airborne visible infrared imaging spectrometer (AVIRIS) data experiments demonstrate that it can effectively detect and classify targets while achieving very high compression ratios.

I. Introduction

In remotely sensed imagery, lossless and lossy compressions have been studied and investigated extensively in the past. In object detection and image classification applications, the accuracy in detection and classification is generally determined by features of objects in the image data rather than the original data. In this case, lossless compression does not provide additional advantages over lossy compression in the sense of feature extraction. Success of a lossy compression technique depends on selecting an appropriate optimal criterion to meet a preset desired goal. In hyperspectral imagery, due to significantly improved spatial and spectral resolution. Many unknown signal sources can be uncovered by hyperspectral sensors for data analysis, some of which may be very important, such as anomalies and small targets in image analysis. Accordingly, preserving desired information is very important to lossy data compression. In this paper we investigate an application of linear spectral mixture analysis (LSMA) in hyperspectral image compression.

The idea of using the LSMA in hyperspectral image compression is appealing from a feature-extraction point of view because it takes advantage of the spectral properties in a pixel of mixed material substances, referred to as targets. Rather than using the whole stack of images in a hyperspectral image cube for compression, the proposed approach replaces the image cube by the abundance fractional images of targets. Because the number of targets is usually smaller than that of spectral bands, a considerable compression can be achieved. Since the primary interest is in feature extraction for image analysis, the abundance fractional images of targets may suffice to preserve the necessary information without sacrificing performance analysis. Since LSMA requires knowledge about the targets of interest in an image scene, a recently developed unsupervised fully constrained least squares linear unmixing (UFCLSLU) method [1] is used to find potential targets in an unknown scene and estimate their corresponding abundance fractions. These abundance fractional images are then used to compress the original image data. Since only targets and their corresponding abundance fractions are required, a high compression ratio can be achieved. In order to evaluate the LSMA-based compression technique, applications in hyperspectral target detection and image classification are considered for performance analysis. The experimental results show that the compression ratio (CR) for AVIRIS data can achieve as high as 76:1 with 34 dB signal-to-noise ratio (SNR) and 46 dB peak SNR (PSNR) after water bands are removed. For 210-band hyperspectral digital imagery collection experiment (HYDICE) data CR can be 126:1, and it is 106:1 after water bands are removed with PSNR greater than 40 dB.

II. Linear Spectral Mixture Analysis (LSMA)

Suppose that L is the number of spectral bands. Let $\mathbf{r}$ be an $L \times 1$ column pixel vector in a multispectral or hyperspectral image, where the bold face is used for vectors. Assume that there are p targets of interest (objects), $\mathbf{t}_1, \mathbf{t}_2, \cdots, \mathbf{t}_p$ in an image scene and let $\mathbf{M}$ be an $L \times p$ target signature matrix denoted by $\left[\mathbf{t}_1 \mathbf{t}_2 \cdots, \mathbf{t}_p\right]$, where $\mathbf{t}_j$ is an $L \times 1$ column vector represented by the signature of the j-th target resident in the pixel $\mathbf{r}$. Let $\boldsymbol{\alpha} = \left[\alpha_1, \alpha_2, \cdots, \alpha_p\right]^T$ be a $p \times 1$ abundance column vector associated with **r,** where α_j denotes the abundance fraction of the *j*-th target signature in **r**. A general approach is to model a pixel vector **r** as a linear mixture of $\mathbf{t}_1, \mathbf{t}_2, \cdots, \mathbf{t}_p$ plus noise:

$$\mathbf{r} = \mathbf{M}\boldsymbol{\alpha} + \mathbf{n}\,, \tag{1}$$

where **n** is noise or can be interpreted as measurement error. Using (1) we can compress the image data by encoding **r** as $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_p]^T$ so that an *L*-band hyperspectral image can be represented by a set of *p* abundance fractional images. Since *p* is usually much smaller than *L* in hyperspectral imagery, a significant compression can be achieved if $\boldsymbol{\alpha}$ can faithfully represent **r**. In order to ensure this, two constraints must be imposed on $\boldsymbol{\alpha}$ in (1), which are (a) abundance sum-to-one constraint, referred to as the ASC, $\alpha_1 + \cdots + \alpha_p = 1$ and (b) abundance nonnegativity constraint, $\alpha_j \geq 0$ for all $1 \leq j \leq p$, referred to as the ANC. In general, no closed-form solution can be derived for (1) subject to constraints ASC and ANC. Fortunately, a fully constrained least squares linear unmixing (FCLSLU) method was recently developed in [1] which can be used to generate the optimal constrained solutions.

III. UFCLSLU

In this section, we will briefly describe the developed fully constrained least squares linear unmixing (FCLSLU) method with details referred to [1]. First, we find the optimal least squares estimate of $\boldsymbol{\alpha}$, $\hat{\boldsymbol{\alpha}}_{LS}$ for model (1) without imposing constraints ASC and ANC. It can be obtained by $\hat{\boldsymbol{\alpha}}_{LS} = (\mathbf{M}^T\mathbf{M})^{-1}\mathbf{M}^T\mathbf{r}$ which will be used for an initial estimate. Next, we impose ANC on model (1) that results in a nonnegatively constrained least squares (NCLS) problem described by

$$\min_{\boldsymbol{\alpha} \geq 0} \left\{ (\mathbf{M}\boldsymbol{\alpha} - \mathbf{r})^T (\mathbf{M}\boldsymbol{\alpha} - \mathbf{r}) \right\}, \tag{2}$$

where $\boldsymbol{\alpha} \geq 0$ represents the non-negativity constraint: $\alpha_j \geq 0$ for all $1 \leq j \leq p$. Since $\boldsymbol{\alpha} \geq 0$ is a set of inequalities, the Lagrange multiplier method is not applicable to solving optimal solutions. An NCLS algorithm developed in [2] can used to solve (2). Further, combining the NCLS algorithm with ASC derives an FCLS algorithm that can reliably estimate $\boldsymbol{\alpha}$ while satisfying both constraints, ANC and ASC [1]. However, the FCLS algorithm requires a complete knowledge of the target signature matrix **M**. In order to use it to compress images, an unsupervised process is needed to generate the desired target information so that the FCLS algorithm is still applicable. A least squares error-based (LSE) unsupervised method was also developed in [1] to implement FCLS algorithm in an unsupervised manner. The method using the resulting algorithm for compression is referred to as UFCLSLU. Using the UFCLSLU we can compress a hyperspectral image cube into a set of *p* abundance fractional images.

The UFCLSLU-based compression method can be described as follows:

1. Use the LSE unsupervised method in [1] to generate a set of potential targets, denoted by $\{\hat{\mathbf{t}}_1, \hat{\mathbf{t}}_2, \cdots, \hat{\mathbf{t}}_p\}$ to form an estimated target signature matrix, denoted by $\hat{\mathbf{M}} = [\hat{\mathbf{t}}_1, \hat{\mathbf{t}}_2, \cdots, \hat{\mathbf{t}}_p]$.
2. For the *i*-th image pixel vector, $\mathbf{r}_i = [r_{i1}, r_{12}, \cdots, r_{iL}]^T$, use the FCLS algorithm to estimate the corresponding target abundance fractions, denoted by, $\{\hat{\alpha}_1(\mathbf{r}_i), \hat{\alpha}_2(\mathbf{r}_i), \cdots, \hat{\alpha}_p(\mathbf{r}_i)\}$
3. Construct *p* abundance fractional images, $\{\hat{\alpha}_1(\mathbf{r}_i), \hat{\alpha}_2(\mathbf{r}_i), \cdots, \hat{\alpha}_p(\mathbf{r}_i)\}$ for the pixel vector $\mathbf{r}_i$.
4. Use any spatial-based coding method such as Huffman coding, DPCM, DCT to encode the *p* abundance fractional images.

The encoded abundance images are stored or transmitted as well as the *p* target signatures. The original data can be reproduced by $\hat{\mathbf{r}}_i = \hat{\mathbf{M}}\hat{\boldsymbol{\alpha}}_i$.

IV. Experiments

In this section, two error criteria, referred to as SNR and PSNR defined in [3] and compression ratio (CR) defined by the ratio of original image file size to compressed file size are used for performance evaluation. The AVIRIS data used in the experiments is a subscene of 200×200 pixels extracted from the upper left corner of the Lunar Crater Volcanic Field (LCVF) in Northern Nye County, Nevada shown in Figure 1. The five signatures of interest in these images are "red oxidized basaltic cinders", "rhyolite", "playa (dry lakebed)", "shade" and "vegetation". Another two methods were used to compare with UFCLSLU-based compression. One is based on Orthogonal Subspace Projection (OSP) result, another referred to as Least

Squares (LS) OSP uses the least squares solution of (1) without imposing any constraints to abundances. These two methods needed the priori information of these 5 signatures. As for UFCLSLU it automatically generated 6 signatures (the additional one is an anomaly). Table 1 tabulates the resulting SNR, PSNR and CR where UFCLSLU produced the best results and achieved the highest SNR, PSNR and CR. Figure 2 shows the classification results based on reproduced images by the two unconstrained supervised methods while Figure 3 was the classification based on UFCLSLU. As shown, no appreciable classification difference results from OSP and LSOSP-based compression. UFCLSLU-based compression can even improve the classification results.

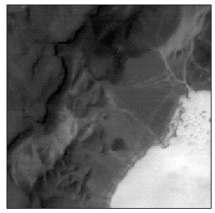
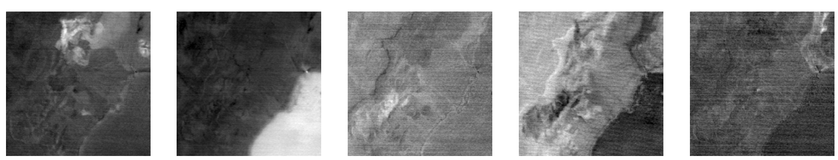


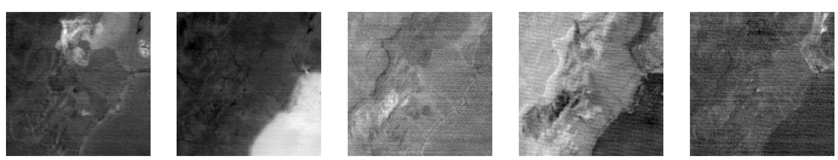
Figure 1. AVIRIS LCVF scene (200x200)

Table 1. SNR, PSNR and CR resulting from three methods

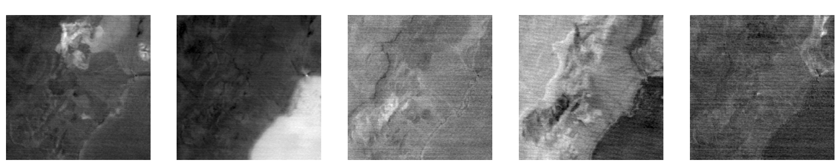
	OSP	**LSOSP**	**UFCLSLU**
SNR(dB)	35.74	35.00	34.98
PSNR(dB)	47.79	47.04	46.03
CR	16.69:1	56.55:1	75.77:1



(a) Using the reproduced image from OSP-based compression

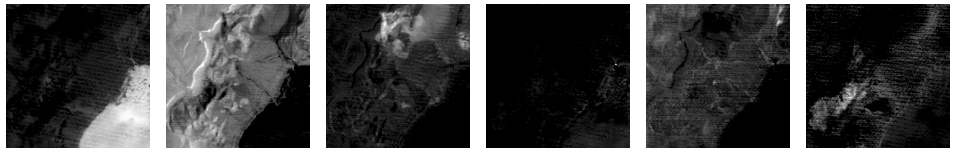


(b) Using the reproduced image from LSOSP-based compression

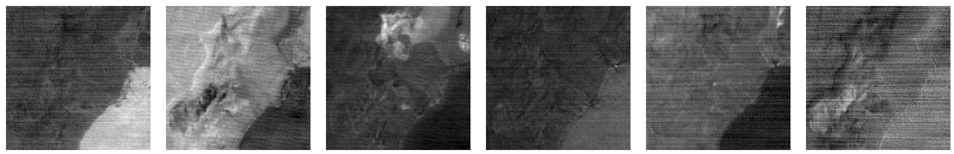


(c) Using the original image (no compression)

Figure 2. The classification results with OSP and LSOSP-based compression (1st column: cinder; 2nd column: playa, 3rd column: rhyolite; 4th column: shade; 5th column: vegetation.)



(a) Using the reproduced image from UFCLSLU-based compression



(b) Using the original image (no compression)

Figure 3. The classification results with UFCLSLU-based compression (1st column: playa; 2nd column: shade; 3rd column: cinder; 4th column: anomaly; 5th column: vegetation; 6th column: rhyolite.)

V. Conclusion

This paper presented a linear mixture analysis-based data compression technique for hyperspectral image analysis. It first identifies potential targets in a hyperspectral image scene in an unsupervised fashion, then compressed the entire image cube using the abundance fractional images of targets present in the image scene. In order to reliably estimate target abundance fractions, an FCLSLU method developed for material quantification in [1] was used. Since the number of targets of interest is generally much smaller than the number of bands in a hyperspectral image, high compression ratio and SNR can be achieved. Furthermore, only abundance fractional images are encoded and unknown signal sources are suppressed by compression. As a result, in some occasions the performance analysis based on the reproduced images can be improved on that yielded by the original images. One major disadvantage of the proposed method is the identification of targets of interest present in an image scene. This has been an unresolved issue and very difficult to solve without prior knowledge.

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References

[1] D. Heinz and C.-I Chang, "Fully constrained least squares linear mixture analysis method for material quantification in hyperspectral imagery," *IEEE Trans. on Geoscience and Remote Sensing*. (revised)

[2] C.-I Chang and D. Heinz, "Subpixel spectral detection for remotely sensed images,"*IEEE Trans. on Geoscience and Remote Sensing*, vol. 38, no. 3, May 2000.

[3] W.K. Pratt, *Digital Image Processing*, 2nd ed., pp.685-686, 1991.