The Impact of Lossy Compression on Hyperspectral Data Adaptive Spectral Unmixing and PCA Classification

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Abstract— In the past, scientific data have been almost exclusively compressed by means of lossless methods, in order to preserve their full quality. However, more recently, there has been an increasing interest in the lossy compression which has not yet globally accepted by the remote sensing community, mainly because it is sensed that the lossy compressed images may affect the results of posterior processing stages. Hence here, the influence of lossy compression on two standard approaches for hyperspectral data exploitation known as adaptive spectral unmixing, and supervised classification using PCA are considered. The experimental result states that the adaptive spectral unmixing provides a user defined spatial scale which improves the process of extraction of end members and PCA improves the classification accuracy. It is also observed that, for certain compression techniques, a higher compression ratio may lead to more accurate classification results. This work further provides recommendations on best practices when applying lossy compression prior to hyperspectral data classification and/or unmixing.

Index Terms— Hyperspectral data lossy compression, end member extraction, adaptive spectral unmixing, wavelet transform, support vector machine (SVM), Principal component analysis

I. INTRODUCTION

Hyperspectral imaging amounts to collect the energy reflected or emitted by ground targets at a typically very high number of wavelengths, resulting in a data cube containing tens to hundreds of bands. These data have become increasingly popular, since they enable plenty of new applications, including detection and identification of surface and atmospheric constituents, analysis of soil type, agriculture and forest monitoring, environmental studies, and military surveillance. In hyperspectral imaging, two types of compression have been investigated extensively in the past [1]. Lossless data compression is generally a type of data compaction, which eliminates *unnecessary* redundancy without loss of any information. While, lossy data compression removes some *low-detail* information. Since the best compression ratios achieved by lossless techniques are in the order of 3:1 [2], Lossy compression is generally used when higher ratios are required and two of the most recent satellites, SPOT 4 and IKONOS, started to employ lossy compression prior to downlinking the data to ground stations. Nevertheless, lossy compression has not yet achieved global acceptance in the remote sensing community, because it is generally sensed that using compressed images may ultimately affect the results of posterior processing stages of remote sensing images, such as spectral unmixing or image classification. This negative effect, however, has been scarcely characterized, mostly in the context of classification applications [1].

By using some approaches like vector quantization (VQ) higher compression ratios of 70:1 were achieved without reducing the classification performance for joint classification and compression of hyperspectral images and here the classification error can be expressed as an alternative to the mean square-error (MSE) distortion measure. Similarly, high classification accuracy can also be obtained at high compression ratios, particularly when a spatial–spectral (wavelet like) transform is applied. This suggests that including spatial information typically improves classification accuracy, even if this information is introduced through image distortion induced by lossy compression.

II. TRANSFORM CODING TECHNIQUES

Transform-based lossy compression has a huge potential for hyperspectral data reduction and the transform techniques considered here are wavelet based. Wavelet-based compression techniques are commonly divided into two functional parts: First,(DWT) decorrelates the input image in the spatial domain, and second, a bit plane encoder (BPE) stage encodes the transformed image, possibly followed by an entropy coder (e.g., a Huffman or an arithmetic encoder). In addition, in order to improve the coding performance of these techniques, a common strategy for hyperspectral images is to decorrelate first the image in the spectral domain; DWT and principal component analysis (PCA) are often used as Group (JPEG). The latest standard of the Joint Photographic Experts group JPEG2000 is also employed along with the DWT. These techniques are able to distribute the target bit rate among the components using a bit allocation algorithm spectral decorrelator [3].

III. EXPERIMENTAL RESULTS

The performance of the different progressive lossy-to-lossless techniques in terms of two hyperspectral data exploitation applications, i.e., adaptive spectral unmixing and PCA classification are evaluated. In all cases, the evaluation has been performed on a representative bit-rate range 0.2–2.0 bits per pixel per band (bpppb), i.e., a compression ratio ranging from 80:1 to 8:1.

A. Adaptive Spectral Unmixing

The hyperspectral scene used for the adaptive spectral unmixing experiments is the well-known AVIRIS Cuprite

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image. The scene comprises 224 spectral bands between 0.4 and 2.5μm, with a spectral resolution of 10 nm. Prior to the analysis, several bands were removed due to water absorption and low signal-to-noise ratio, retaining a total of 188 bands for experiments.

1) Experiment1: Impact of Hyperspectral Data Lossy Compression on Estimation of the abundances.

The method used for estimating the number of abundances from the fundamental materials available in the original data set and in the recovered scenes (after coding and decoding) are evaluated using a method developed by Harsanyi, Farrand, and Chang [4] that includes a noise-whitening process as pre-processing by using three different values of false alarm probability (P_F=10^{-3}, P_F = 10^{-4}, and P_F = 10^{-5}) known as NWHFC. As the compression ratio was increased (low bit rate), the use of DWT for spectral decorrelation severely affected the estimation of the number of abundances by NWHFC. For the NWHFC method, we can observe two performance groups: 1) 3-D compression algorithms (DWT-JPEG2000 and PCA-JPEG2000) were outperformed by the 2-D compression algorithms (TER, JPEG2000, and JPEG2000- BIFR.. A simple statistical measure to evaluate the similarity of the fractional abundances estimated for the same end member in the original and the compressed scene is the root MSE (RMSE).

2) Experiment 2: Impact of Hyperspectral Data Lossy Compression on estimation of number of end members

The method for estimating the number of end members in the original data set and in the recovered scenes is evaluated by using Hysime method. HySime performed differently, in the sense that the compression techniques applying PCA or DWT performed better than the other ones and for this method the most accurate estimates were provided by PCA as spectral decorrelators and the sensitivity to different types and levels of compression is different.

3) Experiment3: Impact of Hyperspectral Data Lossy Compression on End member Extraction:

Here, the number of end members in the AVIRIS scene is assumed as p = 22. With this assumption in mind, 22 end members were extracted from the original and compressed scenes (at different compression ratios) using three popular end member extraction methods [5]: N-FINDR [6], orthogonal subspace projection (OSP), and vertex component analysis (VCA)[7]. Then the quantitative assessment of end member extraction accuracy was conducted by comparing the results obtained by the same end member extraction algorithm applied to the original hyperspectral scene (without compression) and to the scenes obtained after applying different compression techniques. The quantitative measure used for evaluation of end member extraction accuracy was the average spectral angle distance (SAD) between the end members obtained from the original scene and the end members obtained from the compressed scenes with different techniques and compression ratios. The results indicate that the use of PCA or DWT as spectral decorrelator leads to an improvement in the SAD-based scores for all the end member extraction algorithms (with lower values meaning higher spectral similarity). SAD-based similarity scores between the end members extracted from the original AVIRIS data set and the end members extracted after coding the original scene with different compression techniques and compression ratios were measured in radians,. The values have been multiplied by a constant factor of 100 for visualization purposes. To conclude this section, it is emphasized that the impact of compression on different types of pixels such as *pure* (in which the resulting measure is given by the underlying response of one single material), *mixed* (in which the resulting measure is given by the underlying response of several materials), and *anomalous* (with very low occurrence in the scene) did not reveal important differences when assessing the performance of the compression algorithms.

B. PCA Classification

The availability of hyperspectral images expands the capability of using image classification to study detailed characteristics of objects, but at a cost of having to deal with huge data sets. The hyperspectral scene used for PCA classification experiments is the well-known AVIRIS image (in radiance units) .Some bands that are noisy or covering the region of water absorption are removed and finally remaining spectral bands were taken in to account. Before training, data were normalized to give zero mean and unit variance. Only 20% of the available training samples of each class were used for building the model, and the rest was used for testing.

The principal component analysis is based on the fact that neighbouring bands of hyperspectral images are highly correlated and often convey almost the same information about the object. The analysis is used to transform the original data so to remove the correlation among the bands. In the process, the optimum linear combination of the original bands accounting for the variation of pixel values in an image is identified. It employs the statistic properties of hyperspectral bands to examine band dependency or correlation.

The important conclusion is that it can yield about 70 percent correct classification rate and using the principal component analysis technique as a pre-processing step for the classification yields benefit and efficienc

TABLE 1 Area , speed and power for PCA

Power	Area	speed
0.064 w	**1.46700 kilobytes**	**5.277 ns**

TABLE 2 Area, speed and power for SVM

Power	Area	speed
0.099 w	**1.76550 kilobytes**	**7.455 ns**

IV. CONCLUSIONS

In this paper, the impact of different lossy compression techniques on the tasks of hyperspectral image classification and spectral unmixing were examined and implemented using VHDL.VHDL is a hardware description language and in case of VHDL the major considerations are area, speed and power. When taking this into account compared with other techniques like SVM, PCA provides better results. This is shown in TABLE 1 for PCA and in TABLE 2 for SVM.

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