Spectral-Decorrelation Strategies for the Compression of Hyperspectral Imagery

Hrishikesh Tamhankar and James E. Fowler
Department of Electrical and Computer Engineering
GeoResources Institute
Mississippi State University, Mississippi State, MS 39762

***Abstract*— Several linear transforms with constructions more general than that of principal component analysis are considered for spectral decorrelation in the compression of hyperspectral imagery. Specifically, orthogonal nonnegative matrix factorization, generalized principal component analysis, and principal component analysis coupled with explicit segmentation based on spectral angle mapping are considered. These spectral-decorrelation techniques are employed in conjunction with wavelet-based spatial decorrelation for hyperspectral compression using a 3D version of the well-known SPIHT algorithm. A shape-adaptive wavelet transform and shape-adaptive SPIHT coder are used in the case of the latter two spectral-decorrelation techniques which segment the hyperspectral dataset into multiple distinct pixel classes. Experimental results reveal that, despite their general formulation, the proposed techniques fail to offer spectral-decorrelation performance superior to that of traditional principal component analysis.**

I. Introduction

The vast data volumes contained in typical hyperspectral imagery have entailed an increasing interest in lossy compression. Since hyperspectral data exhibits a high degree of correlation not only spatially but also spectrally, a popular paradigm for the compression of hyperspectral imagery consists of the application of some spatial 2D transform applied in conjunction with a separate 1D spectral transform, followed by a suitable 3D image-compression scheme. Quite often, the spatial transform is a 2D discrete wavelet transform (DWT), while a number of techniques have been employed for the spectral transform, including principal component analysis (PCA) (e.g., [1, 2]) and a 1D spectral DWT (e.g., [3]). Part 2 of the JPEG2000 standard [4] supports these and other linear spectral transforms representable as matrix-vector multiplication. Other prominent 3D wavelet-based coders, such as 3D-SPIHT [5], are also easily applied to such "2D+1D" transform decompositions.

PCA, also known as the Karhunen-Loève transform (KLT), has been widely employed for spectral decorrelation in hyperspectral imagery; PCA has exhibited efficient rate-distortion performance in practice for lossy compression, typically outperforming DWT-based spectral decorrelation by a wide margin (e.g., [1, 2]). The use of PCA is also further motivated by the fact that it provides theoretically optimal decorrelation in a certain statistical sense [6]. However, several more general transforms have arisen recently in various applications. In general, fewer constraints imposed on the transform-design procedure translates into greater potential for superior rate-distortion performance, since searching over a larger space of possible transforms can only improve performance.

In this paper, we compare several emerging linear-transform techniques to the established approach of PCA at the task of spectral decorrelation for hyperspectral compression. Specifically, we investigate orthogonal nonnegative matrix factorization (ONMF) [7], generalized principle component analysis (GPCA) [8], and PCA coupled with segmentation into multiple pixel classes based on spectral angle mapping (SAM). We overview each of these techniques in Sec. II and describe their use in 3D-SPIHT for hyperspectral compression in Sec. III. Finally, we present experimental results in Sec. IV and make some concluding remarks in Sec. V.

II. Spectral Decorrelation

In general, a linear transform for decorrelation of N spectral bands is represented by an $N \times N$ matrix. While many transforms (such as a DWT) have a fixed transform regardless of the dataset being coded, others, such as PCA, have a transform matrix which is data-dependent. In this case, a transform-design procedure determines this matrix for the dataset at hand—for PCA, transform design is typically conducted via a singular-value decomposition of the covariance matrix of the dataset. Below we briefly describe several alternatives to PCA that produce linear transforms using a less-constrained design procedure.

A. Orthogonal Nonnegative Matrix Factorization (ONMF)

Nonnegative matrix factorization (NMF), popularized by [9], factors a rectangular matrix D into matrix factors F and G of compatible dimensions such that the elements of all three matrices are nonnegative. NMF employs iterative update rules that minimize a certain objective function such that the original dataset (D, in which each column represents a hyperspectral pixel from the original image) is decomposed by a linear transform of a very general design. In this transform, G is the transform matrix, and F is the matrix of transform coefficients, such that reconstruction results from simple matrix multiplication,

$$D = FG. \tag{1}$$

The ONMF version of NMF [5] imposes a near-orthogonality condition on G to provide a near-orthonormal linear transform

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which is suitable for use as spectral decorrelation in compression tasks.

Matrix factorization appears attractive for spectral decorrelation since its formulation as (1) seems to be minimally constrained—its transform-design procedure simply searches for a transform matrix (G) and a matrix of transform coefficients (F) that reconstruct the original dataset (D). Recently, however, NMF has been shown to be equivalent to k-means clustering, and, consequently, vector quantization [10].

B. Generalized Principle Component Analysis (GPCA)

GPCA, introduced in [8], is an algebraic-geometric tool for segmenting a set of discrete N-dimensional data points into smaller subspaces of equal or lesser dimension. Essentially, GPCA can be viewed as an extension of traditional PCA wherein the data is a union of two or more underlying subspaces, and GPCA provides a non-iterative method to segment the original data into these underlying linear subspaces. Traditional PCA is then applied within each individual subspace.

Spectral decorrelation via PCA can be seen as a special case of GPCA in which the number of classes is constrained to be 1. Being more general, GPCA could potentially outperform traditional single-class PCA by tailoring decorrelation to distinct subspaces within the dataset.

C. PCA Coupled with Explicit Segmentation

In the final strategy, SAM is used to partition the hyperspectral image into a multiple number of pixel classes, with each class being coded independently. SAM [11] has been widely employed in remote-sensing applications to measure the similarity, or "closeness," of a spectral signature (pixel vector) to a fixed reference signature by considering the two spectra to be vectors lying in N-dimensional space, where N is the number of spectral bands, and simply calculating the angle between the two spectra. We follow the blind endmember-extraction methodology of [12] wherein a fixed number of endmembers are extracted from the dataset in a geometrical process that finds the endmembers as vertices of a simplex corresponding to the dataset. Subsequently, each pixel vector from the hyperspectral image is assigned to the class with the corresponding endmember that is closest to the pixel in spectral angle. Then, PCA is applied spectrally to each class separately; we call this approach "SAM+PCA" spectral decorrelation.

III. Methodology

A. Shape-Adaptive Coding

Essentially, GPCA and SAM+PCA differ only in the approach to dataset segmentation, as PCA is applied to each class separately following the segmentation. Additionally, a 2D spatial DWT is applied to each pixel class separately following the spectral PCA. However, in both techniques, the pixel classes form spatial regions in the image that are typically not rectangular and have, instead, some arbitrary shape. As a consequence, the spatial DWT in these techniques is a so-called shape-adaptive DWT (SA-DWT) [13], and the coding applied is shape-adaptive as well, as in [14].

The coding of imagery with shapes more general than rectangular frames has become an important issue in multimedia communications. The straightforward approach to handling arbitrarily shaped image regions (pixel classes) is to consider pixels within the region of interest as "opaque" and those outside the region as "transparent," and to adapt rectangular-frame coders to process only the opaque regions within the bounding box of the region. To this end, in modern embedded wavelet coders, one employs a SA-DWT [13] that transforms only opaque regions in the image. For shape-adaptive SPIHT (SA-SPIHT) coding, transparent regions are considered to be permanently insignificant, as in [15]. In this case, zerotree structures aggregate large regions of transparent coefficients into zerotree symbols along with the opaque insignificant coefficients. A further refinement on this basic approach observes that greater efficiency can be obtained by discarding all sets of coefficients that lie entirely within a transparent region from further consideration [16].

B. Dimensionality Reduction

Since the number of spectrally distinct signal sources composing a given hyperspectral scene is limited, it has been argued that the spectral dimensionality intrinsic to a hyperspectral image is typically much less than the number of spectral bands. Like PCA, each of the spectral-decorrelation strategies considered above (ONMF, GPCA, and SAM+PCA) provides not only spectral decorrelation but also dimensionality reduction. That is, typically a spectral transform is applied, and only a number of "principal components" are retained and coded, the other, insignificant components from the transform being largely noise. The ideal number of components to retain in this dimensionality-reduction step is typically data-dependent (see [1]). For the experiments here, we retain 40 components for PCA; likewise, the ONMF transform matrix G is designed directly with a dimensionality of 40 components, and SAM+PCA consists of 40-component PCA applied in each class. For GPCA, we retain components in each subspace such that the dimensionality of the subspace union is on the order of 15–20, for computational reasons.

IV. Experimental Results

In experimental simulations, a hyperspectral image of spatial dimension 128×128 with 364 spectral bands was collected with the TRWIS III airborne sensor; bands lie in the wavelength range of 380 to 2450 nm. For GPCA, experiments were performed with segmentation into 2 subspaces (GPCA-2), each of dimension 9, as well as 3 subspaces (GPCA-3), each of dimension 5. Likewise, for SAM+PCA, 2, 3, and 4 pixel classes were used (SAM+PCA-2, SAM+PCA-3, and SAM+PCA-4, respectively).

After each spectral-decorrelation technique, a 2D dyadic spatial DWT (or spatial SA-DWT in the case of SAM+PCA or GPCA) is applied to spatially decorrelate the dataset, and then 3D-SPIHT [5] (or 3D-SA-SPIHT in the case of SAM+PCA or GPCA) is used to code the resulting transform coefficients. We use the QccPack (`http://qccpack.sourceforge.net`) implementation of 3D-SPIHT and 3D-SA-SPIHT.

Fig. 1 plots the rate-distortion performance for SPIHT coding applied subsequently to each spectral-decorrelation approach. These experimental results reveal that traditional PCA outperforms the other strategies, although, at the higher rates, all but ONMF offer similar performance. Segmentation, either with GPCA or with SAM, does not appear beneficial, with rate-distortion performance largely deteriorating with increasing number of classes. Finally, ONMF achieves performance significantly inferior to that of the other approaches.

V. Conclusions

In this paper, we have considered several general linear transform methodologies for the spectral decorrelation of hyperspectral imagery for lossy compression. In particular, we have examined an orthogonal matrix factorization (ONMF) as well as two techniques that partition the dataset into several pixel classes and apply PCA to each class separately—GPCA, which is a multiclass generalization of PCA, and SAM+PCA, wherein classes are constructed via spectral angle and explicit endmember extraction. Being more general than PCA, each technique initially appears to offer the potential to outperform traditional PCA in the spectral-decorrelation task. However, experimental results reveal that this is not the case, PCA achieving rate-distortion performance superior to that of the alternative strategies, particularly for low bitrate.

We hypothesize that, although it appears to have the least-constrained formulation, ONMF fails to live up to expectation because such matrix factorizations have been shown to be equivalent to vector quantization which, in turn, is not widely considered to be competitive with state-of-the-art techniques for data compression. Likewise, segmentation, either implicitly via GPCA or explicitly via SAM, does not appear to offer improved performance; we hypothesize that this is due to any benefits in decorrelation arising from the segmentation being outweighed in relative detriments to coding performance due to the shape-adaptive nature of the coding—such costs of shape-adaptive coding have been noted in [17]. As a consequence, traditional PCA outperforms the proposed alternative, and more general, transform constructs for spectral decorrelation in the hyperspectral-compression task.

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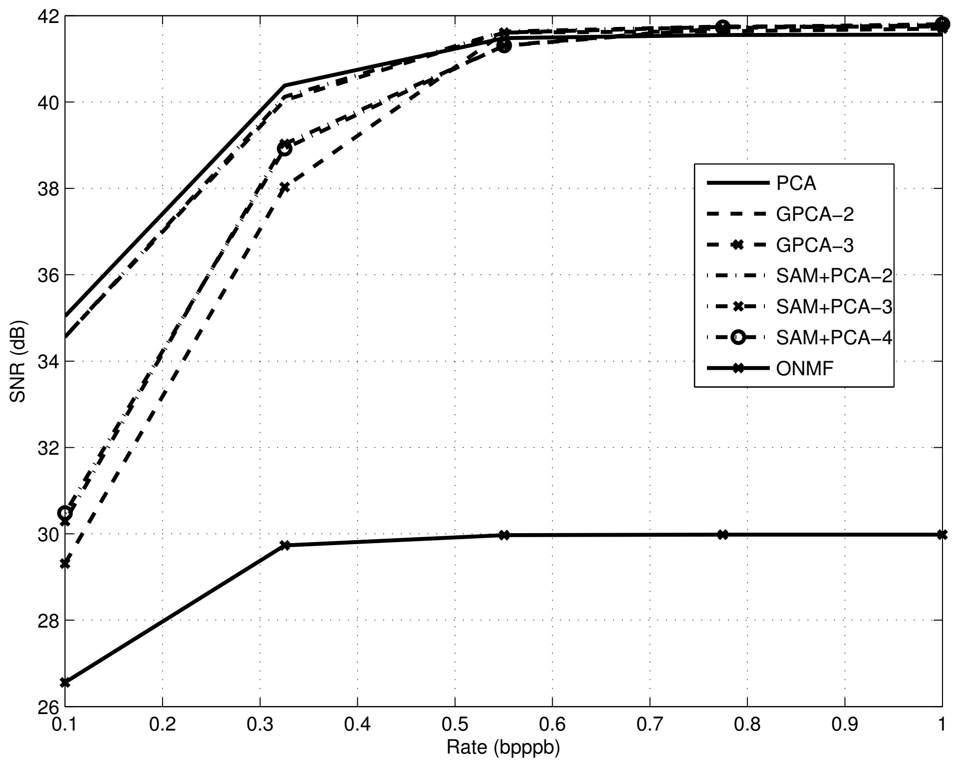

Fig. 1. Signal-to-noise ratio (SNR) at various bitrates in bits per pixel per band (bpppb) for the `northfarm` TRWIS III image.

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