Interference and Noise-Adjusted Principal Components Analysis

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***Abstract*—The goal of principal components analysis (PCA) is to find principal components in accordance with maximum variance of a data matrix. However, it has been shown recently that such variance-based principal components may not adequately represent image quality. As a result, a modified PCA approach based on maximization of SNR was proposed. Called maximum noise fraction (MNF) transformation or noise-adjusted principal components (NAPC) transform, it arranges principal components in decreasing order of image quality rather than variance. One of the major disadvantages of this approach is that the noise covariance matrix must be estimated accurately from the data *a priori*. Another is that the factor of interference is not taken into account in MNF or NAPC in which the interfering effect tends to be more serious than noise in hyperspectral images. In this paper, these two problems are addressed by considering the interference as a separate, unknown signal source, from which an interference and noise-adjusted principal components analysis (INAPCA) can be developed in a manner similar to the one from which the NAPC was derived. Two approaches are proposed for the INAPCA, referred to as signal to interference plus noise ratio-based principal components analysis (SINR-PCA) and interference-annihilated noise-whitened principal components analysis (IANW-PCA). It is shown that if interference is taken care of properly, SINR-PCA and IANW-PCA significantly improve NAPC. In addition, interference annihilation also improves the estimation of the noise covariance matrix. All of these results are compared with NAPC and PCA and are demonstrated by HYDICE data.**

***Index Terms*— Interference annihilation, interference-annihilated noise-whitened principal components analysis (IANW-PCA), interference and noise-adjusted principal components analysis (INAPCA), maximum noise fraction (MNF) transformation, noise-adjusted principal components (NAPC) transform, principal components analysis (PCA), signal to interference plus noise-based principal components analysis (SINR-PCA).**

I. Introduction

PRINCIPAL components analysis (PCA) is a versatile technique and has been used widely in signal processing for various applications such as dimensionality reduction, data compression, and feature extraction. It is of particular interest in multispectral image processing, because it can be used to decorrelate spectral correlation. However, it was shown recently by Green *et al.* in [1] that the variance of multispectral images did not necessarily reflect real SNR, due to unequal noise variances incurred in different bands. As a result, a band with small variance does not necessarily mean poor image quality. It may have a high SNR compared to other bands with large variances but low SNR's. In order to deal with this problem, Green *et al.* developed a maximum noise fraction (MNF) transformation based on maximization of SNR, so that the transformed principal components are ranked by SNR rather than variance as used in a PCA. This MNF transformation was later reinterpreted by Lee *et al.* in [2], using a two-stage process comprised of a noise-whitening process and a PCA to achieve what the MNF transform does. This new derived transform is referred to as a noise-adjusted principal components (NAPC) transform. A standard maximum variance-based PCA simply will be referred to as a PCA throughout this paper. Since noise variances in different bands are whitened by NAPC prior to application of a PCA, maximizing the noise-whitened multispectral data variance results in maximizing their corresponding SNR. Therefore, NAPC is essentially equivalent to MNF and can be viewed as a variant of MNF. In a recent report [3], a fast computation for NAPC also was proposed. In this paper, NAPC will refer either to the MNF transform or to the NAPC transform.

Despite the potential and usefulness of NAPC shown in multispectral imaging processing, one disadvantage of implementing NAPC is that the noise whitening process requires complete knowledge of the noise variances of the data to be processed. More precisely, it requires one to accurately estimate the noise covariance matrix from the data. It is generally difficult to do so, as pointed out in [1], [2]. On the other hand, NAPC does not take interference into consideration. This may not be a problem for multispectral images. However, it was shown in [4], [5] that the effect of interference was more serious than noise in hyperspectral images, and signal-to-interference ratio (SIR) turned out to have more impact on hyperspectral target detection and classification than SNR.

In this paper, we address these two problems by considering interference as a separate, unknown source in addition to signals and noise (e.g., natural background, clutters, etc.). Such interference deteriorates SNR and reduces the accuracy of the noise covariance matrix estimate. It should be taken care of properly prior to data analysis. Since interference represents an unknown source, its knowledge usually is not available *a priori*. Therefore, this information must be obtained in an unsupervised fashion. For this purpose, an unsupervised vector quantization developed in [4], [5] is used to generate a set of possible interferers. Using these generated interferers, an interference and noise-adjusted principal components analysis (INAPCA) can be developed in the same manner that the NAPC was derived in [2].

Manuscript received September 26, 1997; revised April 13, 1998.

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Publisher Item Identifier S 0196-2892(99)06146-X.

Two approaches are suggested for the proposed INAPCA to cope with the interference caused by interferers. One, referred to as signal to interference plus noise ratio-based principal components analysis (SINR-PCA), is to consider signal-to-interference plus noise ratio (SINR) as a criterion to measure image quality rather than SNR, as was used in NAPC. As a result, both interference and noise will be whitened before a PCA transform is applied. The advantage of SINR-PCA is that when interference appears to be a dominant source over noise, as often is the case with hyperspectral images, SINR becomes signal-to-interference ratio (SIR), i.e., SINR $\approx$ SIR. By whitening the interference and noise altogether, SINR-PCA can enhance the NAPC performance, as will be shown in experiments. Because of this, SINR-PCA can be thought of as an improved version of NAPC. A second method, referred to as interference-annihilated noise-whitened principal components analysis (IANW-PCA), is to consider the interference as a separate source so that interference will be annihilated prior to the use of NAPC. It also includes two interference-annihilated versions of PCA and NAPC, referred to as interference annihilated-PCA (IA-PCA) and interference annihilated-NAPC (IA-NAPC), respectively. As can be expected, interference annihilation increases SNR and the accuracy of noise covariance matrix estimation for NAPC, thus greatly improving the performance of NAPC. Accordingly, IANW-PCA extends the capability of NAPC to deal with interference.

The advantage of considering interference separately was evidenced in [4], [5]. In the traditional signal-plus-noise model, the role of interference generally is overlooked. It is either treated as part of the signal or included in noise. This is primarily due to the fact that it is difficult to obtain the knowledge of interference in practice. However, according to experiments conducted for hyperspectral image data in [4]–[6], the interference was shown to be an important factor in target detection and classification. Accordingly, estimating the noise covariance matrix without eliminating the signal and interference may lead to an inaccurate and biased estimate. In order to annihilate the signal and interference, an orthogonal projection developed in [7] is applied before the noise covariance matrix is estimated. It projects all image pixel vectors onto a space that is orthogonal to signals and interference so as to achieve signal suppression and interference annihilation. Then, the resulting orthogonal complement space will be used as the desired noise subspace from which the noise covariance matrix can be estimated easily by sample covariance matrix (SCM).

Several advantages can be gained by INAPCA. In hyperspectral images, many unwanted interferers that cannot be resolved by multispectral imagers can now be picked up by hyperspectral sensors. Under this circumstance, the SINR criterion is more appropriate than SNR. Or SNR still can be used for a criterion after interference is annihilated. In either case, separating and eliminating these interferers from noise and signals certainly can improve traditional SNR-based methods. In addition, no prior knowledge is required for INAPCA. This is indeed a very significant advantage, because it can be implemented in an unknown environment without knowing the background.

The remainder of this paper is organized as follows. In Section II, NAPC is reviewed briefly, and Roger's approach [3] is described. In Section III, an SINR model is introduced to derive the INAPCA, and two approaches, SINR-PCA and IANW-PCA are proposed to implement the INAPCA. In Section IV, experiments are presented using hyperspectral digital imagery collection experiment (HYDICE) image data to demonstrate the advantages of the INAPCA over NAPC. In Section V, a brief conclusion is drawn.

Typographic Conventions

Throughout this paper, vectors are denoted by boldface lowercase letters or boldface Greek lowercase letters, matrices or spaces are denoted by italic uppercase letters or Greek uppercase letters, and transpose and matrix inverse are denoted by superscripts T and -1. The italic I denotes the identity. $\langle\cdot\rangle$ denotes a linearly spanned space, and $\langle\cdot\rangle^{\perp}$ is the space orthogonal to $\langle\cdot\rangle$.

II. NAPC Transform

As shown in [1], the principal components resulting from a maximum variance-based PCA do not necessarily represent image quality. Because of that, Green *et al.* proposed the MNF transform so that the transformed principal components are arranged by SNR rather than variance. The MNF was rederived later in [2] as an NAPC in terms of noise-whitening processing. However, the NAPC transform described later follows the approach recently proposed for a fast NAPC transform in [3].

Consider the observation model

$$\boldsymbol{z} = \boldsymbol{s} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{z}$ is an observation vector with the covariance matrix denoted by $\Sigma_{\boldsymbol{z}}$. $\boldsymbol{s}$ is a signal vector, and $\boldsymbol{n}$ is the noise vector independent of $\boldsymbol{s}$, with the covariance matrix denoted by $\Sigma_{\boldsymbol{n}}$. Now assume that the matrix F is the noise-whitening matrix which orthonormalizes $\Sigma_{\boldsymbol{n}}$ such that

$$F^T \Sigma_{\boldsymbol{n}} F = I \quad \text{and} \quad F^T F = \Delta_{\boldsymbol{n}}^{-1}. \tag{2}$$

$\Delta_{\boldsymbol{n}}$ in (2) is the diagonal matrix of the eigenvalues of $\Sigma_{\boldsymbol{n}}$. It should be noted that the F can be obtained by $F = E\Delta_{\boldsymbol{n}}^{-1/2}$ where E is a transform such that $E^T\ \Sigma_{\boldsymbol{n}}\ E = \Delta_{\boldsymbol{n}}$.

Then, transforming $\Sigma_{\boldsymbol{z}}$ by F, i.e., $\Sigma_{\text{adj}} = F^T\ \Sigma_{\boldsymbol{z}} F$, gives rise to a noise-adjusted data covariance matrix denoted by Σ_{adj}. Let G be the eigenvector matrix resulting from a PCA based on Σ_{adj}. Then, we obtain

$$G^T \Sigma_{\text{adj}} G = \Lambda_{\text{adj}} \quad \text{and} \quad G^T G = I \tag{3}$$

where $\Lambda_{\text{adj}} = \text{diag}\{\lambda_{\text{adj},i}\}$ is the diagonal matrix of the eigenvalues $\{\lambda_{\text{adj},i}\}_{i=1}^{l}$ of Σ_{adj}. Finally, the desired NAPC transform can be derived by

$$H = GF. \tag{4}$$

In other words, NAPC can be implemented by a two-stage process [specified by H in (4)] comprised of a first-stage process using F given by (2) to whiten the noise, and a second stage process using G given by (3) to perform a PCA transform.

III. Interference and Noise Adjusted Principal Components Analysis (INAPCA)

Equation (1) is a signal model that is corrupted by noise, and upon which NAPC is based. It is a standard signal-plus-noise model considered in communications/signal processing. There is no interference specified in (1). However, the model given by (1) may not be appropriate for hyperspectral images (as demonstrated in [4], [5]), since many unknown interferers now may be present and picked up in hyperspectral imagers due to significantly increased spectral resolution, e.g., 10 nm compared to multispectral resolutions ranging from 100 to 400 nm. As a result, including interference in (1) as a separate third source has shown a substantial advantage in hyperspectral image processing, since it can be used to enhance and improve SNR in [4], [5]. By separating interference from the model given by (1), an SINR model can be expressed as

$$\boldsymbol{z} = \boldsymbol{s} + \boldsymbol{i} + \boldsymbol{n}. \tag{5}$$

Based on (5), an analogous derivation to NAPC for adjusting noise specified by (1)–(3), NAPC also can be applied to derive an INAPCA for adjusting interference and noise. Two approaches, referred to as SINR-PCA and IANW-PCA, then will be proposed for the INAPCA to take care of interference and noise prior to the use of PCA and NAPC. Here, we use the noise whitened (NW) in the IANW-PCA instead of the noise adjusted (NA) used in the NAPC to emphasize the nature of the noise whitening processing implemented in IANW-PCA.

A. Signal to Interference Plus Noise Ratio-Based Principal Components Analysis (SINR-PCA)

The SINR-PCA presented in this section is an improved version of NAPC transform where the SNR is replaced by SINR. In this case, we assume that either the interference is part of the noise, or the noise energy is very small compared to the interference energy, so that SINR is approximately equal to SIR (i.e., SINR $\approx$ SIR). The idea of SINR-PCA is to identify signals from the data before an estimate of the noise covariance matrix takes place. This can be done by visual inspection or an unsupervised method such as vector quantization described in the following section.

Equation (5) is a generic model for signal processing. Of particular interest in multispectral/hyperspectral image processing are linear mixing problems where (5) can be used to model a mixture linearly mixed by signals residing in a pixel. To be more specific, we assume that M, denoted by $M = (\boldsymbol{s}_1 \boldsymbol{s}_2 \cdots \boldsymbol{s}_p)$, is a signal matrix consisting of p linearly independent L-dimensional signal vectors $\{\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_p\}$ present in a pixel vector $\boldsymbol{z}$. We further assume that p (i.e., the number of signals) are less than the data dimensionality. Let $\alpha_i = (\alpha_{i1}\alpha_{i2}\cdots\alpha_{ip})^T$ be a $p \times 1$ abundance column vector associated with M where α_{ij} denotes the abundance concentration of the jth signal $\boldsymbol{s}_j$ in the observation pixel vector $\boldsymbol{z}$. Similarly, let $\Psi = (\boldsymbol{i}_1 \boldsymbol{i}_2 \cdots \boldsymbol{i}_q)$ be the interference matrix where $\boldsymbol{i}_k$ is the kth interference signature and $\phi = (\phi_1 \phi_2 \cdots \phi_q)^T$ is the corresponding abundance vector of the interference signals in Ψ. In this manner, (5) can be rewritten as

$$\boldsymbol{z} = \boldsymbol{s} + \boldsymbol{i} + \boldsymbol{n} = M\alpha + \Psi\phi + \boldsymbol{n} \tag{6}$$

where $\boldsymbol{s} = M\alpha$ is an L-dimensional signal vector linearly mixed by p signal vectors $\{\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_p\}$, and $\boldsymbol{i} = \Psi\phi$ is an L-dimensional interference vector linearly mixed by q interferers $\{\boldsymbol{i}_1 \boldsymbol{i}_2 \cdots \boldsymbol{i}_q\}$.

Based on (6), an algorithm of implementing SINR-PCA transform can be described as follows.

Stage 1. *Annihilating signals*: Apply an orthogonal subspace projector $P_M^{\perp}$ in [7] given by

$$P_M^{\perp} = I - MM^{\#}. \tag{7}$$

The $M^{\#} = (M^T M)^{-1} M^T$ in (7) is the pseudo-inverse of M, and the notation $^{\perp}_{M}$ in $P_M^{\perp}$ indicates that the projector $P_M^{\perp}$ maps the observed pixel vector $\boldsymbol{z}$ into the range space $\langle M \rangle^{\perp}$, the orthogonal complement of $\langle M \rangle$ where the notation $\langle X \rangle$ represents the space linearly spanned by X. Let $\langle M \rangle^{\perp} = \langle \{P_M^{\perp}\boldsymbol{z} | \boldsymbol{z} \text{ are all image pixel vectors}\} \rangle$.

Stage 2. *Estimating the interference/noise covariance matrix* $\Sigma_{\boldsymbol{i}+\boldsymbol{n}}$: The $\langle M \rangle^{\perp}$ obtained from (7) in Stage 1 is the desired interference-plus-noise subspace, is orthogonal to $\langle M \rangle$, and will be used to estimate the interference/noise covariance matrix denoted by $\Sigma_{\boldsymbol{i}+\boldsymbol{n}}$. Since signals have been either suppressed or annihilated in the space $\langle M \rangle^{\perp}$, a standard simple technique of using the SCM [8] can be used to estimate $\Sigma_{\boldsymbol{i}+\boldsymbol{n}}$. It should be noted that in general, $\langle M \rangle^{\perp}$ is not of full rank, since it is suppressed by (7).

Stage 3. *Whitening* $\Sigma_{\boldsymbol{i}+\boldsymbol{n}}$: Use (2) to whiten $\Sigma_{\boldsymbol{i}+\boldsymbol{n}}$, obtained in Stage 2, then apply a PCA transform described by (3). The desired SINR-PCA is then specified by (4).

B. Unsupervised Vector Quantization

The SINR-PCA described above considered the interference and noise together as an entity, with no need to discriminate between interference and noise. The advantage of this approach is that it does not require one to find any interferers except signals. However, if the noise energy cannot be ignored in the SINR-PCA transform, the interference must be separated from the noise. So extracting interferers present in the data is necessary.

In (6), the interference $\boldsymbol{i}$ is assumed to be known. Unfortunately, the knowledge of $\boldsymbol{i}$ is generally not available in practice and must be obtained from the data. In this section, an unsupervised vector quantization-based clustering process is proposed to automatically generate a set of interferers designated for $\boldsymbol{i}$ in (6). The only assumption made in this approach is that the number of interferers must be given *a priori*. However, this number can be determined by rank curves proposed in [4]. The vector quantization procedure used for interferers generation is based on the well-known Linde–Buzo–Gray (LBG) algorithm [10], and the criterion used for optimality is the mean-squared error (MSE).

For the Unsupervised Vector Quantization (VQ) Algorithm, assume that q is the number of codewords to be generated for a codebook.

Stage 1. *Initialization*: $\text{Code}^1 = \{\boldsymbol{x}_j^1\}_{J=1}^q$ where $\{\boldsymbol{x}_j^1\}_{j=1}^q$ is a set of q initial clusters generated by an algorithm in [11].

Stage 2. *Iterative procedure for reclustering at step $i > 1$ to generate the ith codebook $Code^i = \{\boldsymbol{x}_j^i\}_{j=1}^q$*:

$$\boldsymbol{x}_j^i = E[X | X \in R_j^{i-1}] \tag{8}$$

where R_j^{i-1} is the jth cluster produced by the codebook at step $i-1$, $\text{Code}^{i-1} = \{\boldsymbol{x}_j^{i-1}\}_{j=1}^q$.

Stage 3. *Stopping rule*: The reclustering will be terminated when no more data vectors are shuffled from one cluster to another. More specifically, as the algorithm iterates, the MSE between data vectors and their nearest cluster centers will be reduced until there is no change in the codebook. As a result, either the MSE's in two consecutive iterations remain unchanged, or their difference is below a prescribed threshold. In this case, no data vector will be shuffled.

C. Interference-Annihilated Noise-Whitened Principal Components Analysis (IANW-PCA)

Unlike SINR-PCA, the IANW-PCA presented here treats the interference as an unwanted source and annihilates it before a PCA or an NAPC transform is applied. Therefore, it can be regarded as a generalization of NAPC. The interference can be characterized by interferers, which are generated by the unsupervised VQ described above. In order to accomplish interference annihilation, a similar orthogonal projector specified by (6) also can be used for this purpose.

Assume that the interference vector $\boldsymbol{i}$ in (6) is mixed by q interferers $\{\boldsymbol{i}_1, \boldsymbol{i}_2, \cdots, \boldsymbol{i}_q\}$ generated by an unsupervised VQ. The following algorithm describes a procedure to implement the IANW-PCA that applies an NAPC transform to the interference-annihilated space $\langle \Psi \rangle^\perp$ where the noise covariance matrix $\Sigma_{(M\Psi)^\perp}$ is estimated by the SCM in the space $\langle M\Psi \rangle^\perp$ orthogonal to the signal matrix $M = (\boldsymbol{s}_1 \boldsymbol{s}_2 \cdots \boldsymbol{s}_p)$ and the interference matrix $\Psi = (\boldsymbol{i}_1 \boldsymbol{i}_2 \cdots \boldsymbol{i}_q)$.

Stage 1. *Finding interference-annihilated space $\langle \Psi \rangle^\perp$*: Apply an orthogonal subspace projector $P_U^\perp$ similar to (7)

$$P_U^\perp = I - UU^\# \tag{9}$$

with $U = \Psi$. Let $\langle \Psi \rangle^\perp = \langle \{P_\Psi^\perp \boldsymbol{z} | \boldsymbol{z}$ are all image pixel vectors$\} \rangle$.

Stage 2. *Estimating noise covariance matrix $\Sigma_{(M\Psi)^\perp}$ in space $\langle M\Psi \rangle^\perp$*: Apply $P_U^\perp$ in (9) again with $U = (M\Psi) = (\boldsymbol{s}_1 \boldsymbol{s}_2 \cdots, \boldsymbol{s}_P \boldsymbol{i}_p \boldsymbol{i}_1 \boldsymbol{i}_2 \cdots \boldsymbol{i}_q)$. Let $\langle M\Psi \rangle^\perp = \langle \{P_{M\Psi}^\perp \boldsymbol{z} | \boldsymbol{z}$ are all image pixel vectors$\} \rangle$. In the space $\langle M\Psi \rangle^\perp$, the signals and interferers either have been suppressed or annihilated. It supposedly contains only noise, and the noise covariance matrix can be estimated directly from this noise subspace by the SCM. As can be expected, $\Sigma_{(M\Psi)^\perp}$ will be more accurate than $\Sigma_{\boldsymbol{n}}$ estimated by the NAPC from the entire space Z. Let $\Sigma_{(M\Psi)^\perp}$ be the noise covariance matrix estimate.

Step 3. *Applying an NAPC transform to the orthogonal complement space of Ψ, i.e., $\langle \Psi \rangle^\perp$ with $\Sigma_{\boldsymbol{n}}$ in (2), replaced by $\Sigma_{(M\Psi)^\perp}$*: The desired IANW-PCA is then specified by (4). It should be noted that because M and Ψ are not generally orthogonal, it requires one to orthognalize Ψ for IANW-PCA with respect to M prior to finding $\langle \Psi \rangle^\perp$. A standard Gram-Schmidt orthogonalization procedure can be used for this purpose. Orthogonalization is needed, because we use (9) to annihilate interference via orthogonal projection. If M and Ψ are not orthogonal, the part of M projected onto the space $\langle \Psi \rangle$ will be used as an interference for annihilation. As a result, the signal strength of M will be reduced in the space $\langle \Psi \rangle^\perp$. However, it does not require the orthogonalization procedure for finding $\Sigma_{(M\Psi)^\perp}$.

It should be noted that the idea of IANW-PCA easily can be applied to PCA and NAPC by implementing both transforms in a space with interference annihilated. The resulting transforms (IA-PCA and IA-NAPC) will significantly improve their performance without interference annihilation, as demonstrated in the experiments in Section IV.

Two salient differences between the SINR-PCA and the IANW-PCA are worth mentioning. One is the noise subspace from which the noise covariance matrix is estimated in Stage 2. The IANW-PCA uses the orthogonal complement space $\langle M\Psi \rangle^\perp$, within which both the signals in M and the interferers in Ψ are suppressed or annihilated rather than the signal-annihilated space $\langle M \rangle^\perp$ used in the SINR-PCA. In the SINR-PCA, the interference and noise are considered as an entity. The other difference is the space to which a PCA transform is applied in Stage 3. The SINR-PCA applies an NAPC transform to the original observation space Z, whereas the IANW-PCA applies an NAPC transform to the interference-annihilated space $\langle \Psi \rangle^\perp$.

IV. EXPERIMENTS

In this section, a set of designed experiments using HYDICE images are presented. The HYDICE scene used for experiments is shown in Fig. 1 (image of band 30), which was taken in Maryland in August 1995 using 210 bands with 10 nm spectral resolution and spectral coverage 0.4–2.5 μ m. The ground sampling distance (GSD) is approximately 0.78 m. The figure has a size of 128×128 and shows a large grass field with tree lines running along the left edge. This field contains a road running along the right edge of the image. There are four vehicles vertically aligned. The top three are treaded vehicles, and the bottom one is a wheeled vehicle. The size of the treaded vehicles is approximately 4 m by 8 m, and the size of the wheeled vehicle is about 3 m by 6 m. In addition to these vehicles, there is an object located in the center of the scene.

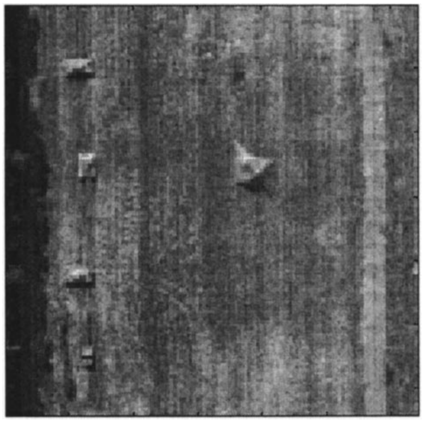


Fig. 1. Scene of the HYDICE image of band 30.

The experiments conducted in the first example were based on 11 bands uniformly selected from the 210 HYDICE band images that were composed to generate a multispectral HYDICE image. This composed, eleven-band image was used to study INAPCA for the case in which the interference was considered part of noise, i.e., SINR-PCA. The second example was designed to evaluate the effect of interference on PCA and NAPC when a full set of 210 HYDICE band images were used for experiments. In particular, we will demonstrate in this example that the proposed INAPCA significantly improves PCA and NAPC in image representation using principal components. Additionally, we will show that PCA and NAPC do not work well unless interference is annihilated.

Example 1 (Multispectral Images): In this example, eleven bands were selected uniformly from 210 bands, and these eleven band images were used to study the problem addressed in [1]. There, ten band images were used. It started the first image with ten band images and then followed it with 20 bands apart. This experiment demonstrates the advantage of SINR-PCA over PCA and NAPC when SINR is considered instead of SNR. From the image scene in Fig. 1, eight signals can be identified visually. There are four vehicles (three treaded vehicles on the top and one wheeled vehicle at the bottom) parked along the tree line corresponding to the four blobs in a vertical line to the left of the image, one man-made object corresponding to a blob located to the right and just above the image center, three natural background signals, a road corresponding to the bright strip to the right of the image, a grass field corresponding to greyish background, and a tree line corresponding to the dark left strip. Although there are also two concentric semicircular arcs located at the bottom half on the left, they are vehicle tracks on the grass field and can be viewed as part of the grass field. So we assume that the signal matrix M comprises eight signals: three treaded vehicles, one wheeled vehicle, one object, a road, grass, and a tree. The orthogonal complement space $\langle M\rangle^{\perp}$ will be used as the interference-plus-noise space which needs to be whitened in SINR-PCA. For the experiments considered in this example, two noise estimate methods were used for NAPC. They were the near-neighbor differences (NND) in [1], [2, p. 298], which can be implemented by taking the difference between two adjacent pixels along horizontal lines in the same fashion DPCM used in image coding and the residual-scaled PC (RPC) transform developed by Roger in [9]. They hereafter will be referred to as NAPC/NND and NAPC/RPC, respectively. Fig. 2(a)–(d) shows the results of 11 principal components (PC's) produced by a standard maximum variance-based PCA, NAPC/NND, NAPC/RPC, and SINR-PCA, respectively. As can be seen, all four transforms perform comparably, and their first seven PC's extract very much the same information. It is interesting to note that NAPC/RPC produced very different fourth and fifth PC's compared to those produced by the other three. However, the information represented by these two PC's appears to be extracted already by the first three PC's. So from this point of view, NAPC/RPC does not offer a useful advantage for information extraction. However, from a target-detection point of view, NAPC/RPC does show four vehicles in the fourth PC, and most of the unwanted signals are nulled-out from the background. Similarly, the object and wheeled vehicle were clearly detected in the seventh PC. Two observations can be made from this experiment. One is that there are no apparent advantages yielded by NAPC and SINR-PCA over PCA in multispectral images, as shown in Fig. 2. The other is that, from Fig. 2(d), SINR-PCA did not demonstrate an advantage to using SINR over SNR. This suggests that interference does not have appreciable effects on multispectral images. Instead, the noise seems to be a more important factor than interference in multispectral image processing. A similar conclusion also was derived by using 70 band images uniformly selected from the 210 band images, a case corresponding to 64 band images considered in [2]. However, this assertion is no longer true for hyperspectral imaging processing, as will be demonstrated in the following example.

Example 2 (Hyperspectral Images): Unlike Example 1, where interference was not considered separately, this example used the full set of 210 HYDICE band images to conduct a series of experiments to examine both the effect of interference on the estimation of noise covariance matrix and the advantage of using interference-annihilated space $\langle\Psi\rangle^{\perp}$. It was shown in [4] that ten was an adequate number of interferers for the image scene in Fig. 1. Thus, a total of at least 18 bands is required for experiments to accommodate these ten interferers plus eight signals in M, each for one dimension [12]. Using the supervised VQ described in Section III-A, ten interferers for Ψ were generated.

Two proposed SINR-PCA and IANW-PCA approaches for INAPCA will be compared against PCA and Lee *et al.*'s NAPC (Green *et al.*'s MNF) transform. Throughout the rest of this paper, as long as NAPC is used without a suffix, we refer to either NAPC/NND or NAPC/RPC. Also included in comparison are an IA-PCA and an IA-NAPC. The IA-PCA applies PCA to the interference-annihilated data space $\langle\Psi\rangle^{\perp}$ instead of the original data space Z. Similarly, IA-NAPC also applies NAPC to $\langle\Psi\rangle^{\perp}$, with the noise covariance matrix estimated by either NND or RPC in $\langle\Psi\rangle^{\perp}$, denoted by IA-NAPC/NND and IA-NAPC/RPC, respectively. The reason for introducing IA-PCA and IA-NAPC for comparison is to evaluate the impact on PCA and NAPC if interference is annihilated and also to see how much improvement can be

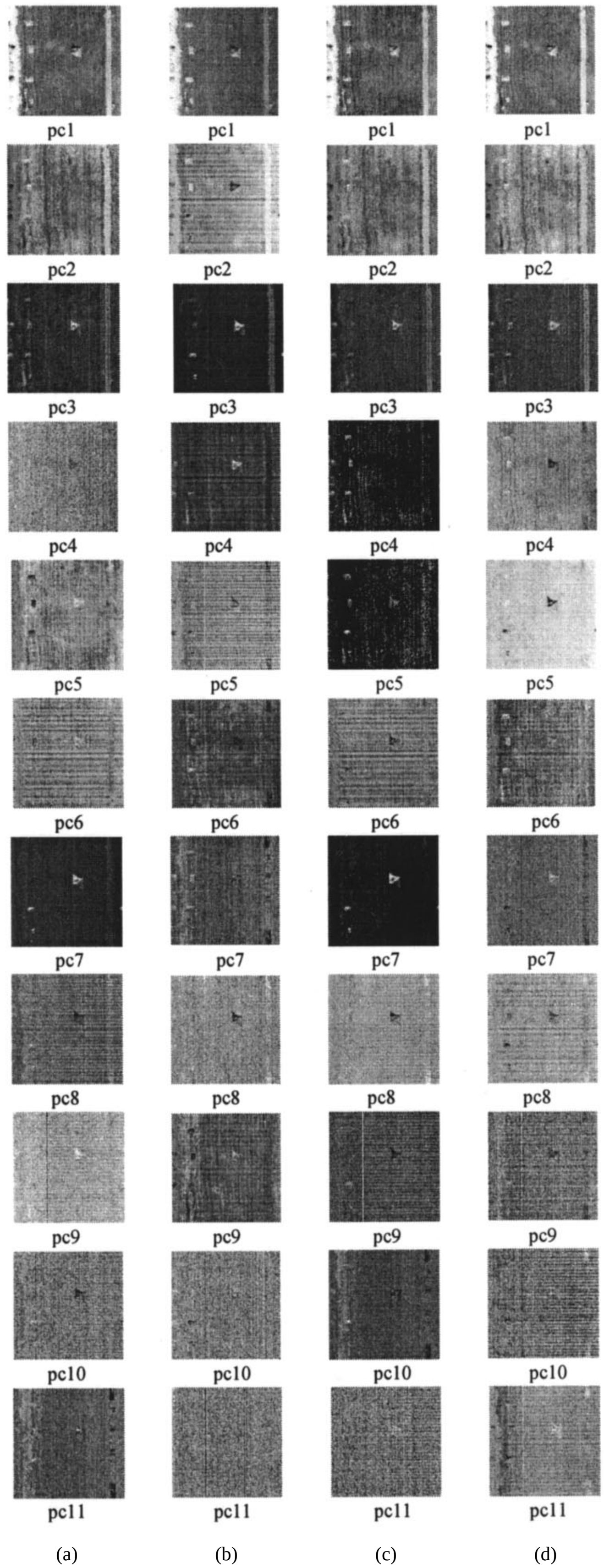


Fig. 2. Eleven principal components of an eleven-band multispectral image derived from the hyperspectral image in Fig. 1. (a) Eleven principal components produced by PCA. (b) Eleven principal components produced by NAPC/NND. (c) Eleven principal components produced by NAPC/RPC. (d) Eleven principal components produced by SINR-PCA.

made upon them without interference annihilation. Therefore, a total of eight experiments were conducted, one for each PCA, NAPC/NND, NAPC/RPC, IA-PCA, IA-NAPC/NND, IA-NAPC/RPC, IANW-PCA, and SINR-PCA.

Fig. 3(a)–(h) shows nine principal components (PC's) generated by these eight transforms: PCA, NAPC/NND, NAPC/RPC, IA-PCA, IA-NAPC/NND, IA-NAPC/RPC, IANW-PCA, and SINR-PCA, respectively. As shown in these eight figures, the best results were produced by the transforms: IA-PCA, IA-NAPC/NND, IA-NAPC/RPC, IANW-PCA, SINR-PCA (which take extra care with regard to interference). This also demonstrated the advantage of using interference annihilation. If we compare their results to those in Fig. 3(a)–(c) (produced by the transforms disregarding interference: PCA, NAPC/NND, and NAPC/RPC), we find the former compacts most of the image information into the first six PC's [as shown in Fig. 3(d)–(h)], while the latter spreads out the image information over the nine PC's. Of particular prominence is that the image quality produced by PCA and NAPC is greatly improved by their counterparts IA-PCA and IA-NAPC. A surprising discovery is that NAPC/NND yielded the worst results among all the images in Fig. 3, and it was even worse than PCA without adjusting the noise. However, if we compare the results produced by NAPC/RPC, the image quality is considerably better. This observation further points out noise estimate as an important parameter of implementing NAPC. Specifically, the performance of NAPC depends heavily on the accuracy of noise estimate to be used in NAPC.

Another striking finding is that if we apply PCA to an interference annihilated space, the resulting image quality of PC's can be improved considerably [as shown in Fig. 3(d)] and are even better than those produced by NAPC without interference annihilation [shown in Fig. 3(b)–(c)]. This suggests that the interference becomes more dominant than noise in hyperspectral images, so that the SNR criterion used for NAPC offers no advantages over PCA. In this case, SINR may be a better criterion since the interference can be used to account for part of data variance but noise cannot. Comparing the results in Example 1, where SINR-PCA did not show its superiority to PCA and NAPC in multispectral images, this example shows that SINR-PCA clearly outperformed PCA and NAPC in hyperspectral images. This result further supports the claim made in [4]: that interference is more crucial than noise in hyperspectral image analysis and cannot be ignored as in multispectral imaging processing.

When we compare the images in Fig. 3(d)–(h) produced by PCA-like transforms with interference annihilation, it is difficult to judge which one is the best by visual inspection. However, according to our data-driven experience, IANW-PCA is our favorite from a target detection and classification point of view. In its first PC, most of the information was extracted (including eight signals). This gives us an overview of targets of interest. It is then followed by its second PC (showing the large grass field), while its third and fourth PC's pick up man-made targets (the four vehicles and the object, respectively). In fact, all transforms except NAPC/NND extracted eight signals in their first PC's. Nevertheless, our

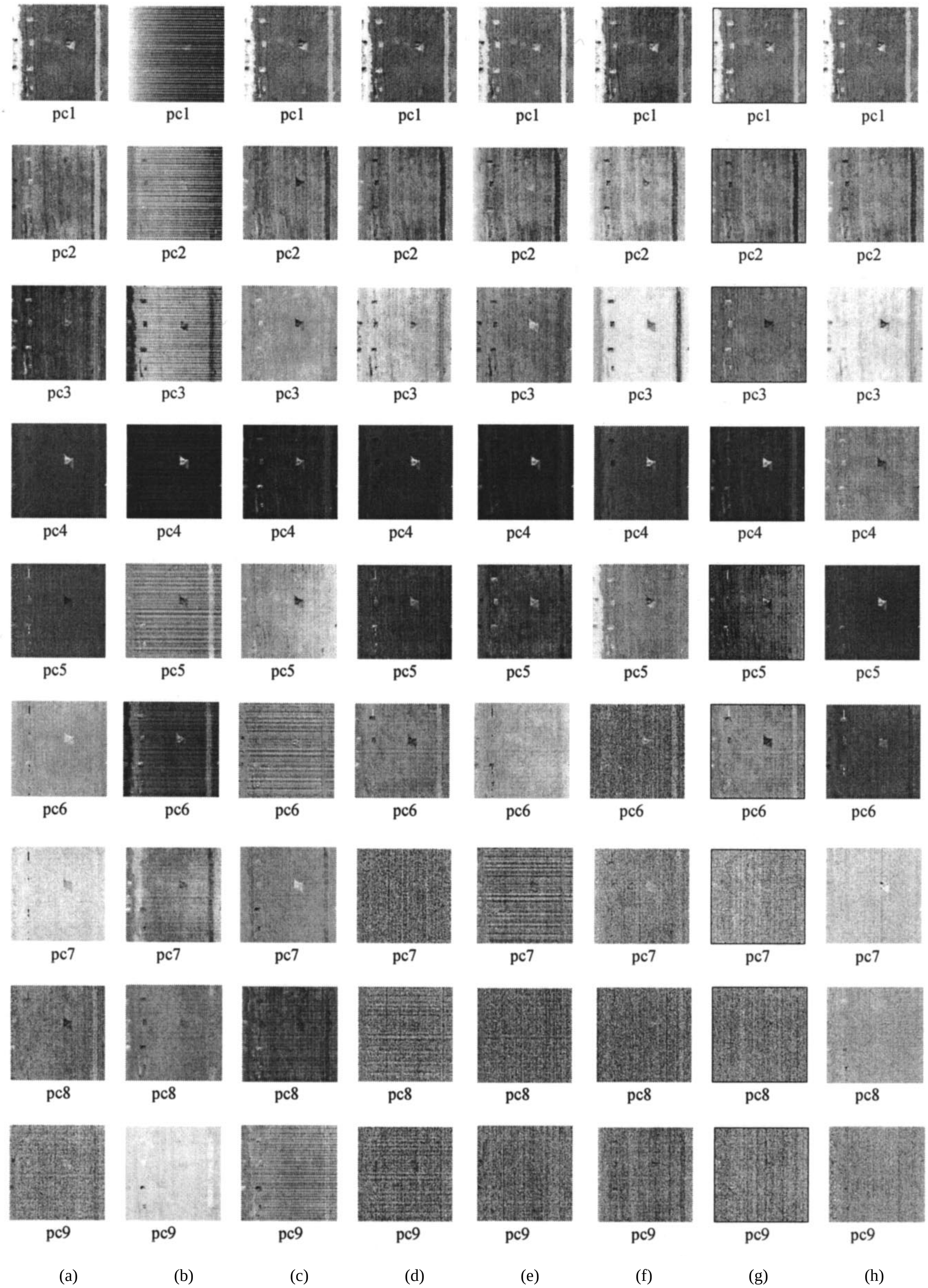
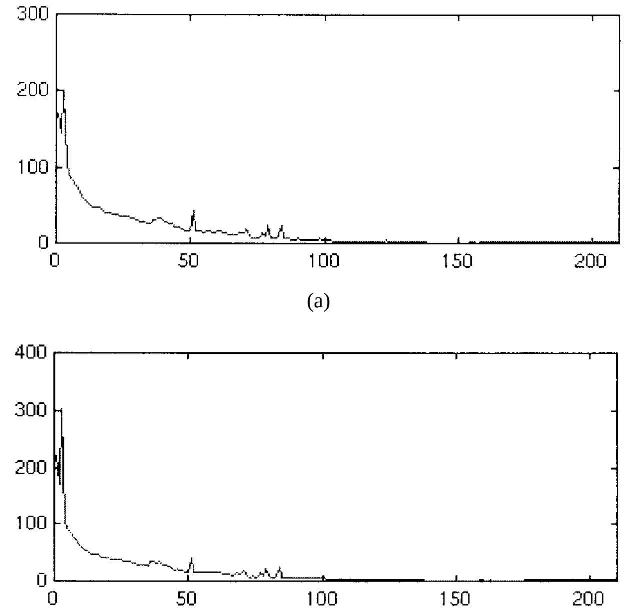


Fig. 3. Nine principal components of the 210-band hyperspectral image in Fig. 1. (a) Nine principal components produced by PCA. (b) Nine principal components produced by NAPC/NND. (c) Nine principal components produced by NAPC/RPC. (d) Nine principal components produced by IA-PCA. (e) Nine principal components produced by IA-NAPC/NND. (f) Nine principal components produced by IA-NAPC/RPC. (g) Nine principal components produced by IANW-PCA. (h) Nine principal components produced by SINR-PCA.

preference is somewhat subjective and does not imply that IANW-PCA is the best among the eight transforms. However, the study in this example did demonstrate an important fact: that IA-PCA could perform as well as other PCA-like transforms did in an interference-annihilated space. This actually suggests that IA-PCA may best fit general applications. Since PCA is a widely used, versatile technique, it is very simple to implement and does not require noise estimate.

It should be noted that there is a broken line along the vehicles shown in some PC's of Fig. 3(a) (PCA), 3(d) (IA-PCA), 3(e) (IA-NAPC/NND), 3(g) (IANW-PCA), and 3(h) (SINR-PCA), but not shown in any PC of NAPC/NND and NAPC/RPC. This broken line is caused by a strong interferer due to a scratch in the HYDICE sensor during the flight, and it actually occurs in only a few of the 210 bands. Despite interference in nature, it still represents a piece of information and must be retained in some PC's in terms of information conservation. Although SINR-PCA does not directly annihilate interference, it does manage to adjust both interference and noise together by a whitening process in the orthogonal complement of signal space $\langle M\rangle^{\perp}$ so that the interference can be taken care of properly by using SINR rather than SNR. As a consequence, the results in Fig. 3(h) are much better than those in Fig. 3(a)–(c) (which did not take interference into account).

There is a noteworthy comment on the noise estimate used in NAPC. In SINR-PCA and IANW-PCA, the noise simply was estimated by the SCM. This is because $\langle \Psi\rangle^{\perp}$ can be viewed as the sole interference-plus-noise space for SINR-PCA and $\langle M\Psi\rangle^{\perp}$ as the sole noise space for IANW-PCA. So in this case, SCM is a natural choice for noise estimation. On the other hand, NND's were used to estimate the noise in Lee *et al.*'s NAPC and Green *et al.*'s MNF. According to the above experiments, NND turned out to be a poor noise estimator. In contrast, Roger's RPC was an effective noise estimator. As shown, the performance of NAPC could be improved significantly by making use of better noise estimators such as the RPC. However, there is a limit to which an improvement can be made. That is exactly the main point we would like to address by introducing interference annihilation in this example. What we are interested in is the impact and effect of interference on various PCA-based transforms used for hyperspectral images. As a matter of fact, this example also shows that NAPC and RPC can be improved even further by estimating noise variances in an interference-annihilated space. In order to see that, we followed a similar analysis done in [9] and plotted the estimates of noise standard deviations, band standard deviations, and SNR in Figs. 4–6, respectively, for the image scene in Fig. 1. These curves were obtained by applying RPC to the original data space Z and applying RPC to the interference annihilated space $\langle \Psi\rangle^{\perp}$ referred to as IA-RPC. They were plotted in different scales because of large deviations in magnitude. The figures labeled by (a) are results generated by using RPC, while figures labeled by (b) are generated by IA-RPC. As we can see, there is not much difference between Fig. 4(a) and (b), because the interference does not affect the noise. However, as shown in Fig. 5(a) and (b), the band standard deviation is greatly reduced if the interference is annihilated. This result further confirms the



(a)

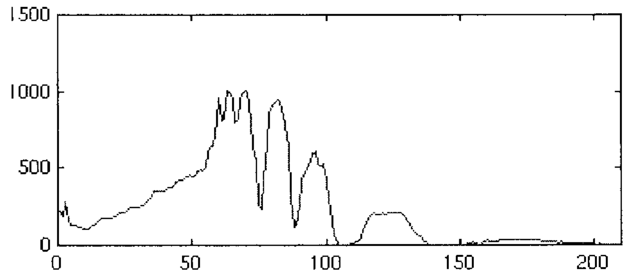
(b)

Fig. 4. Estimates of noise standard deviations for a 210-band HYDICE image. (a) Using RPC. (b) Using IA-RPC.

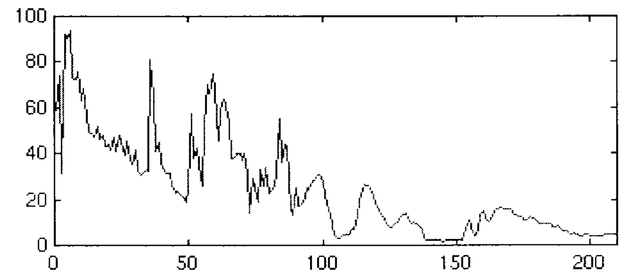
observation, made previously, that the data variance becomes more dominant than noise in hyperspectral images, and that the interference contributes significantly to the reduction of between-band variance. Fig. 6(a) and (b) also demonstrates an interesting result, in which the SNR produced by RPC is higher than that produced by IA-RPC. Such phenomenon occurs because, without interference annihilation, the interference will be considered part of the signals in the image scene, thus increasing the SNR. Most importantly, all the experiments conducted in this example provide clear evidence that the interference has a substantial role in hyperspectral image analysis. It cannot be overlooked and must be taken care of properly.

Before concluding this section, four remarks are in order.

1) By virtue of the noise estimate, IANW-PCA also can be viewed as a variant of NAPC, in which the noise covariance matrix is estimated by SCM in a space in which the signals and interference are annihilated. With this interpretation, IANW-PCA can be referred to as Signal/Interference Annihilated-NAPC/SCM (SIA-NAPC/SCM). Consequently, by also including IA-NAPC as another variant of NAPC, we have five various NAPC-based transforms studied in this paper, two NAPC transforms (NAPC/NND and NAPC/RPC) that have noise estimated in the original data space by NND and RPC, respectively, two NAPC transforms (IA-NAPC/NND and IA-NAPC/RPC) that have the noise estimated in the interference annihilated space $\langle \Psi\rangle^{\perp}$ by NND and RPC, respectively, and the fifth NAPC transform, SIA-NAPC/SCM, that has the noise estimated by SCM in the signal and interference-annihilated space $\langle M\Psi\rangle^{\perp}$.
2) The second remark is on the horizontal striations shown in several PC's in Fig. 3 [particularly 1–6 PC's in

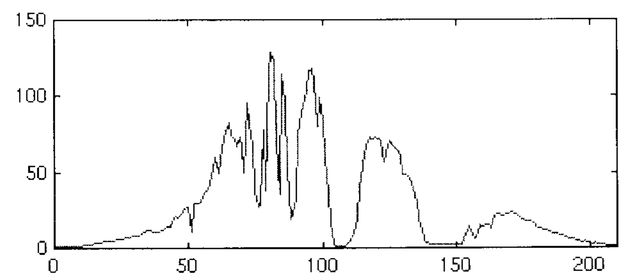


(a)

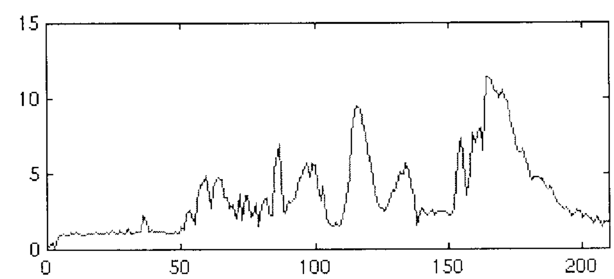


(b)

Fig. 5. Band standard deviation for the 210-band HYDICE image in Fig. 1. (a) Using RPC. (b) Using IA-RPC.



(a)



(b)

Fig. 6. SNR for the 210-band HYDICE image in Fig. 1. (a) Using RPC. (b) Using IA-RPC.

Fig. 3(b)]. This may be due to the inherent spatial structure in the image scene, which cannot be suppressed solely by the spectral-decorrelation-based PCA transforms presented in this paper. Another explanation is that this also may be due to the fact that the NND used was implemented by taking the difference of two horizontal, adjacent pixels, which results in horizontal striations. One feasible way to resolve this problem is to consider the spatial and spectral structures as a whole with the hyperspectral image treated as an image cube. Such an idea also was explored in [14] and in data compression [15].

3) The third remark is on the eleven-band multispectral image used in Example 1. It comprises bands uniformly selected among the 210 HYDICE bands. This uniform band selection is not necessarily optimal. A better band selection suggested in [13] also was used for experiments. The classification results were a little bit better, but the same conclusion still holds.
4) The fourth remark is on the image scene used for the experiments. Several HYDICE image scenes also were evaluated for the various PCA-based transforms. The results were analogous to those presented here, allowing the same conclusion to be drawn.

V. Conclusion

In this paper, an INAPCA was presented. Two approaches resulting from the INAPCA were derived, one called SINR-PCA and the other called IANW-PCA. The SINR-PCA treats the interference as part of the noise, so that a noise-whitening process is performed on both noise and interference. As a result, SINR-PCA produces better image quality in the principal components than PCA and NAPC in hyperspectral images. Unlike SINR-PCA, IANW-PCA considers the interference as a separate, unknown source, so that it can be annihilated prior to PCA or NAPC transform. By means of interference annihilation, PCA and NAPC can be modified further by IA-PCA and IA-NAPC, which implement PCA and NAPC in an annihilated space. These two transforms, together with IANW-PCA and SINR-PCA, significantly improve the performance of PCA and NAPC. Since interference tends to be more dominant than noise in hyperspectral images, INAPCA shows advantages over PCA and NAPC.

Acknowledgment

The authors would like to thank an anonymous reviewer who suggested [9].

References

[1] A. A. Green, M. Berman, P. Switzer, and M. D. Craig, "A transformation for ordering multispectral data in terms of image quality with implications for noise removal," *IEEE Trans. Geosci. Remote Sensing*, vol. 26, pp. 65–74, Jan. 1988.
[2] J. B. Lee, A. S. Woodyatt, and M. Berman, "Enhancement of high spectral resolution remote sensing data by a noise-adjusted principal components transform," *IEEE Trans. Geosci. Remote Sensing*, vol. 28, pp. 295–304, May 1990.
[3] R. E. Roger, "A fast way to compute the noise-adjusted principal components transform matrix," *IEEE Trans. Geosci. Remote Sensing*, vol. 32, pp. 1194–1196, Nov. 1994.
[4] C.-I. Chang, T.-L. Sun, and M. L. G. Althouse, "An unsupervised interference rejection approach to target detection and classification for hyperspectral imagery," *Opt. Eng.*, vol. 37, pp. 735–743, Mar. 1998.
[5] C.-I. Chang and C. Brumbley, "An orthogonalization target signature space projection approach to image classification in unknown background," in *Proc. 31st Conf. Information Sciences and Systems*, Johns Hopkins University, Baltimore, MD, Mar. 1997, pp. 174–178.
[6] C. Brumbley and C.-I. Chang, "An unsupervised vector quantization-based target subspace projection approach to mixed pixel detection and classification in unknown background for remotely sensed imagery," *Pattern Recognit.*, vol. 32, pp. 1161–1174, July 1999.

[7] J. C. Harsanyi and C.-I. Chang, "Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection," *IEEE Trans. Geosci. Remote Sensing*, vol. 32, pp. 779–785, July 1994.
[8] H. V. Poor, *An Introduction to Signal Detection and Estimation*, 2nd ed. New York: Springer-Verlag, 1994.
[9] R. E. Roger, "Principal components transform with simple, automatic noise adjustment," *Int. J. Remote Sensing*, vol. 17, no. 14, pp. 2719–2727, 1996.
[10] Y. Linde, A. Buzo, and R. M. Gray, "An algorithm for vector quantizer design," *IEEE Trans. Commun.*, vol. COMM-28, pp. 84–95, Jan. 1980.
[11] I. Katsavounides, C. C. J. Kuo, and Z. Zhang, "A new initialization technique for generalization Lloyd iteration," *IEEE Trans. Signal Processing Lett.*, vol. 1, pp. 144–146, Oct. 1994.
[12] C.-I. Chang and C. Brumbley, "A Kalman filtering approach to multispectral image classification and detection of changes in signature abundance," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 257–268, Jan. 1999.
[13] C.-I. Chang, Q. Du, T.-L. Sun, and M. L. G. Althouse, "A joint band prioritization and band decorrelation approach to band selection for hyperspectral image classification," submitted for publication.
[14] R. E. Roger and J. F. Arnold, "Reliability estimating the noise in AVIRIS hyperspectral images," *Int. J. Remote Sensing*, vol. 17, no. 10, pp. 1951–1962, 1996.
[15] S.-e. Qian, A. B. Hollinger, D. Williams, and D. Manak, "Fast three-dimensional data compression of hyperspectral imagery using vector quantization with spectral-feature-based binary coding," *Opt. Eng.*, vol. 35, no. 11, pp. 3242–3249, Nov. 1996.

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