Denoising of Hyperspectral Imagery Using Principal Component Analysis and Wavelet Shrinkage

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***Abstract*—In this paper, a new denoising method is proposed for hyperspectral data cubes that already have a reasonably good signal-to-noise ratio (SNR) (such as 600 : 1). Given this level of the SNR, the noise level of the data cubes is relatively low. The conventional image denoising methods are likely to remove the fine features of the data cubes during the denoising process. We propose to decorrelate the image information of hyperspectral data cubes from the noise by using principal component analysis (PCA) and removing the noise in the low-energy PCA output channels. The first PCA output channels contain a majority of the total energy of a data cube, and the rest PCA output channels contain a small amount of energy. It is believed that the low-energy channels also contain a large amount of noise. Removing noise in the low-energy PCA output channels will not harm the fine features of the data cubes. A 2-D bivariate wavelet thresholding method is used to remove the noise for low-energy PCA channels, and a 1-D dual-tree complex wavelet transform denoising method is used to remove the noise of the spectrum of each pixel of the data cube. Experimental results demonstrated that the proposed denoising method produces better denoising results than other denoising methods published in the literature.**

***Index Terms*—Denoising, hyperspectral imagery, principal component analysis (PCA), wavelet shrinkage.**

I. Introduction

NOISE in acquired hyperspectral data cubes presents a challenge to traditional remote sensing applications, including information extraction and scene interpretation. The basic procedure of wavelet denoising is to transform the noisy data cube into wavelet coefficients in the wavelet domain, threshold the wavelet coefficients, and then perform the inverse wavelet transform to obtain the denoised data cube. The thresholding may be undertaken on a term-by-term basis or by considering the influence of other wavelet coefficients on the wavelet coefficients to be thresholded. For term-by-term denoising, the readers can be referred to [1]–[3].

Here, a brief review is given for the most popular wavelet denoising methods. Cai and Silverman [4] proposed a thresholding scheme for signal denoising by taking the immediate neighbor coefficients into account. They claimed that this approach gives better results over the traditional term-by-term approach for both translation invariant (TI) and non-TI single wavelet denoising. Chen and Bui [5] extended this neighboring wavelet thresholding idea to the multiwavelet case. They claimed that neighbor multiwavelet denoising outperforms neighbor single wavelet denoising and the term-by-term multiwavelet denoising [6] for some standard test signals and real-life signals. Chen *et al.* [7] proposed an image denoising scheme by considering a square neighborhood window in the wavelet domain. Chen *et al.* [8] also considered a square neighborhood window and tried to customize the wavelet filter and the threshold for image denoising. Experimental results show that both methods produce better denoising results. Mihcak *et al.* [9] performed an approximate maximum *a posteriori* estimation of the variance for each coefficient, using the observed noisy data in a local neighborhood. Then, an approximate minimum mean squared error estimation procedure is used to denoise the noisy image coefficients. Sendur and Selesnick [10], [11] developed a bivariate shrinkage function for image denoising. Their results showed that the estimated wavelet coefficients depend on the parent coefficients. The smaller the parent coefficients, the greater the shrinkage is. Crouse *et al.* [12] developed a framework for statistical signal processing based on wavelet-domain hidden Markov models. This framework enables them to concisely model the non-Gaussian statistics of individual wavelet coefficients and capture statistical dependencies between coefficients. Simoncelli and Adelson [13] proposed a Bayesian wavelet coring approach by incorporating the higher-order statistical regularity present in the point statistics of subband representation. Chen and Qian [14], [15] proposed to combine wavelet denoising with dimensionality reduction for hyperspectral imagery by using bivariate wavelet thresholding, wavelet packets, and principal component analysis (PCA). Othman and Qian [16] developed a noise reduction algorithm [hybrid spatial-spectral noise-reduction algorithm (HSSNR)] for hyperspectral data cube. The algorithm resorts to the spectral derivative domain, where the noise level is elevated, and benefits from the dissimilarity of the signal regularity in the spatial and spectral domains. Letexier and Bourennane [17] proposed a generalized multidimensional Wiener filter for denoising hyperspectral images. Suksmono and Hirose [18] developed a new adaptive noise reduction method for interferometric synthetic aperture radar complex-amplitude images. In recent years, there has been a major effort to improve the denoising methods. This includes the Bayes least squares-Gaussian scale mixtures (BLS-GSM) method [19], the bivariate Laplacian mixture technique [20], and the local polynomial approximation-intersection of confidence intervals technique [21]. More recently, significant improvement has also

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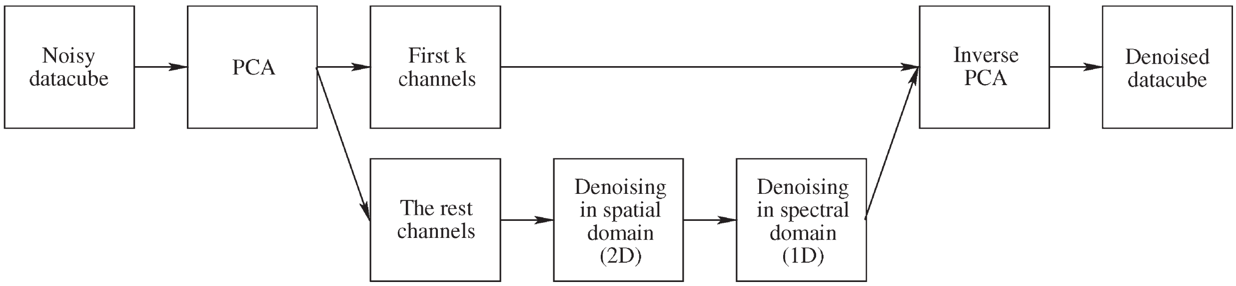

Fig. 1. Flow chart of the proposed denoising method for hyperspectral imagery by using the PCA transform.

been developed by using anisotropic windows around each coefficient [21]–[23]. Chen and Zhu [24] proposed a signal denoising method by using neighboring dual-tree complex wavelet coefficients.

A key parameter in the design of a hyperspectral imager is its signal-to-noise ratio (SNR), which determines the capabilities and cost of the imager. A sufficiently high SNR can be achieved first hand by adopting some excessive measures in the instrument design, e.g., increasing the size of the optical system, increasing the integration time, increasing the detector area, etc. Normally, these are prohibitively expensive solutions, particularly in the case of spaceborne instruments. Alternatively, noise reduction (denoising) algorithms provide a cost-effective solution that is becoming more and more affordable (in terms of speed and expense) due to the availability of the advanced computing devices. Experiments have been carried out to assess the effectiveness of an earlier developed denoising algorithm by the authors [26]–[28]. Intermediate remote sensing products were used based on two evaluation approaches. The first approach relies on narrow-band vegetation indices and red-edge positions, while the second approach adopts a number of spectral similarity measures. Evaluation results show that the denoising algorithm shows comparable results to existing denoising algorithms for vegetation indices, red-edge positions, and superior results for spectral similarity measures [26]. A target detection was chosen as an example of application to evaluate the impact of the denoising algorithm. The experimental results showed that small targets that are missed due to inadequate SNR and spatial resolution of the sensor can be detected after the denoising is applied to the original data [27], [28]. Our previous study [29] showed that, for 3-D data cube, it is necessary to perform 1-D spectral signature denoising in addition to 2-D denoising for every spectral band. Previous simulation showed that 3-D denoising obtains much better results than performing 2-D spectral band denoising alone.

In this paper, a new noise reduction method is proposed by using PCA to decorrelate the fine features of the data cube from the noise. The method does not denoise the first k PCA output channels, where these channels have a much higher percentage of the total energy of the data cube. It removes the noise in each PCA output channel beyond the first k channels. Bivariate wavelet thresholding is used in denoising the low-energy PCA output channels. Also, a new 1-D signal denoising method is proposed by using the dual-tree complex wavelet transform and considering a small neighborhood during the thresholding process. Experimental results show that the proposed denoising method outperforms other denoising methods published in the literature for hyperspectral data cubes. It is well known that the BLS-GSM method [19] generates better denoising results than Sendur's method. However, it is much slower than Sendur's method in terms of CPU time. This is the main reason why we chose Sendur's method in this paper. Since hyperspectral data cubes contain a huge amount of data, it is prohibitive to use the BLS-GSM method in this paper.

The paper is organized as follows. Section II proposes a new denoising method for hyperspectral imagery by using the PCA and wavelet shrinkage. Section III shows the experiments conducted in order to show that the proposed denoising method is promising compared to other denoising methods published in the literature. Finally, Section IV draws the conclusion.

II. New Denoising Method for Hyperspectral Imagery

In this section, we study new wavelet-based denoising methods for reducing noise in hyperspectral data. These methods should be good in preserving the fine features in the hyperspectral data cube while removing as much noise as possible. If denoising is done on the original data cube, then the fine features in the data cube could be lost. This is undesirable in practical applications, such as classification. In this paper, we propose to transform the original data cube to be denoised into another domain and to remove the noise in the low-energy channels in the transformed domain. It is believed that after a proper transformation, the useful features of the original data cube and the noise must be well-separated. By denoising the transformed channels with low energy, better denoising results should be obtained. Fig. 1 shows the flow chart of the proposed denoising method for a hyperspectral data cube by using the PCA transform and wavelet shrinkage.

In this paper, we use a PCA transform. PCA is a widely used dimensionality reduction technique in data analysis [30]. It computes the low-dimensional representation of a high-dimensional data set that most faithfully preserves its covariance structure. One needs to solve the eigenvalues and eigenvectors of the covariance matrix. The outputs of PCA are simply the coordinates of the input patterns in this subspace, using the directions specified by these eigenvectors as the principal axes. The first few principal components (PCs) contain the most information, and the remaining PCs contain much less information.

Even though the first k PCA output channels contain significant percentage of the total energy, it is believed that these channels also contain a small amount of noise. If denoising is performed on these k output channels, then it will remove the useful fine features of the data cube. This is undesirable. In this paper, denoising is only conducted on the rest PCA output channels $k+1, k+2, \ldots, D$, where D is the total number of spectral bands in the original data cube. It should be mentioned that the PCA transform used in this paper keeps all D output channels when applied to the original hyperspectral data cube.

The denoising of the PCA transformed data cube is done in two steps: 1) 2-D denoising of the PCA low-energy output channels; and 2) 1-D denoising of the spectral signatures of every pixel of the scene. The denoising of PCA low-energy output channels can be done by using Sendur and Selesnick's bivariate wavelet thresholding [11] because this method is one of the best image denoising methods in the literature. This method exploits the parent–child relationship in wavelet coefficients, and it is very efficient in terms of both computational complexity and peak SNR values.

For any given wavelet coefficient w_1, let w_2 be the parent of w_1 and define

$$y = w + n \tag{1}$$

where $w = (w_1, w_2)$ denotes the noise-free wavelet coefficients, $y = (y_1, y_2)$ denotes the noisy coefficients, and $n = (n_1, n_2)$ denotes the Gaussian white noise. The 2-D bivariate thresholding formula is given by

$$w_1 = y_1 \cdot \left(1 - \frac{\frac{\sqrt{3}}{\sigma}\sigma_n^2}{\sqrt{y_1^2 + y_2^2}}\right)_+ \tag{2}$$

where $(x)_+ = \max(x, 0)$. The noise variance σ_n [25] can be approximated as $\sigma_n = median(|y_{1i}|)/0.6745$, $y_{1i} \in subband\ HH_1$, and

$$\sigma = \sqrt{\left(\frac{1}{M}\sum_{y_{1i}\in S} y_{1i}^2 - \sigma_n^2\right)_+}. \tag{3}$$

The HH_1 is the finest 2-D wavelet coefficient subband, and M is the number of pixels in the 2-D neighborhood window S. In this paper, a neighborhood of 7 × 7 is chosen in the experiments.

For the 1-D denoising of the spectral signatures of every pixel in the scene, the thresholding of the spectral coefficients can be done in the following way. Suppose that the first k PCA output channels contain significant amount of features, then, for each pixel spectrum, only the spectrum values beyond the first k channels $(y_{k+1}, y_{k+2}, \ldots, y_D)$ will be the input for 1-D spectrum denoising. We can use the single wavelet transform, the multiwavelet transform, or the dual-tree complex wavelet transform for pixel spectrum denoising. The thresholding may use term-by-term based method or consider a small neighborhood. In this paper, the following spectrum denoising method is proposed. The dual-tree complex wavelet transform has the property of approximate shift invariance that is very important in spectrum denoising. Just as the ordinary wavelet transform, the dual-tree complex wavelet transform also produces correlated wavelet coefficients in a small neighborhood. A large complex wavelet coefficient in magnitude will likely have large complex wavelet coefficients in magnitude at its neighboring locations. Therefore, it is desirable to design a thresholding formula that not only uses the current complex wavelet coefficient but also uses the neighboring complex wavelet coefficients. In this paper, we propose to use the following thresholding formula to threshold the wavelet coefficient $d_{j,k}$:

$$d_{j,k} = d_{j,k}\left(1 - \frac{thr^2}{S_{j,k}^2}\right)_+ \tag{4}$$

where $S_{j,k}^2 = (|d_{j,k-1}|^2 + |d_{j,k}|^2 + |d_{j,k+1}|^2)/3$ is the average of $|d_{j,k}|^2$ and $thr = \sqrt{2\sigma_n^2 \log n}$ is the universal threshold. The '$+$' sign at the end of the formula means to keep the value if it is positive, and set it to zero otherwise. The above thresholding formula uses the magnitude of the complex wavelet coefficients, since it is shift invariant even though the real and imaginary parts are not individually so. As we use the current complex wavelet coefficient and its left and right neighbors in the thresholding formula, the neighborhood window size is set to 1 × 3. Although one could use a larger neighborhood size such as 1 × 5, 1 × 7, 1 × 9, etc., for thresholding, our experimental results show that the neighborhood window size of 1 × 3 is the best for denoising noisy spectra.

The computational complexity of the proposed method can be analyzed as follows. The complexity of the wavelet transform is in the order of O(MN), where M is the number of pixels in the spatial domain and N is the number of bands in the spectral domain. The complexity of the PCA is in the order of $O(MN^2 + N^3 + kMN)$, where M and N are defined as before and k is the number of the kept components in the dimensionality reduced data cube. Therefore, the computational complexity of the proposed method is in the order of $O(MN^2 + N^3 + kMN)$ just as for PCA.

Spaceborne hyperspectral imagers cover a wide range of application areas including agriculture, geology, oceanography, forestry and target detection, etc. The SNR of 600 : 1 is the best SNR that can be achieved for a spaceborne hyperspectral imager with the currently available technology and reasonable cost. This value of SNR is the result of a comprehensive tradeoff study by taking into account the requirements from the user community and government departments. There are lots of challenges to achieve this level of SNR from the point of view of instrument design and building. This value of SNR meets the requirements for most of the users. It is desirable to have even better SNR for the users who require higher SNR for their applications. For example, the forest users strongly push for high SNR in order for them to extract information from hyperspectral data using forest chemistry approaches for monitoring the forest health and invasion of insects.

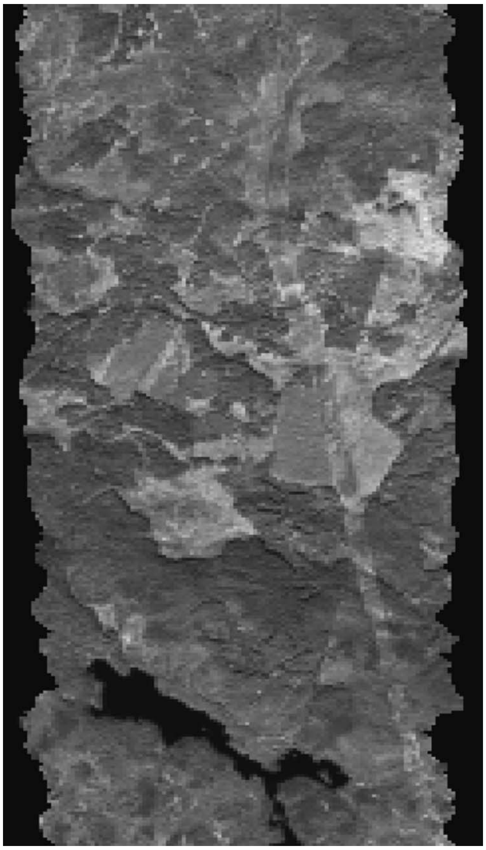

Fig. 2. AVIRIS GVWD scene (spectral band #50).

An instrument with 600 : 1 SNR will never reach the same performance as an instrument with 2000 : 1 SNR whatever how well a denoising technique is and how hard one works on it. Denoising is a promising technology for removing noise in satellite images and gaining additional SNR. The validation and assessment of the effectiveness of this particular denoising technique are yet to be carried out.

III. Experimental Results

In this section, experiments were conducted to demonstrate the feasibility of the proposed denoising method for hyperspectral imagery by using two data cubes. These two data cubes cover two different sites: a vegetation-dominated site and a geological site. The first data cube is acquired using the Airborne Visible/Infrared Imagining Spectrometer (AVIRIS) in the Greater Victoria Watershed District (GVWD), Canada, on August 12, 2002. The ground sample distance (GSD) of the data cube is 4 m $\times$ 4 m with nominal AVIRIS SNR of 1000 : 1. The term *nominal SNR* refers to the ratio of the signal to the noise in the visible and near infrared region in a given SNR pattern at certain circumstances [31]. The data cube was processed to at-sensor radiance and 16-bit encoded. A 28 m $\times$ 28 m GSD data cube was derived by spatially averaging the 4 m $\times$ 4 m GSD data cube elevating the nominal SNR to 7000 : 1. Having such high SNR, this data cube is viewed as a noise-free data cube and is used as a reference to measure the SNR before and after denoising. The corresponding noisy data cube is extracted by adding simulated noise to the reference data cube according to a 600 : 1 SNR pattern in [31]. This noise added data cube is used as a test data cube (referred to as the test noisy data cube) in the experiments. The size of the data cube extracted for testing is 292 $\times$ 121 pixels with 204 spectral bands. Fig. 2 shows band #50 of the original noise-free data cube.

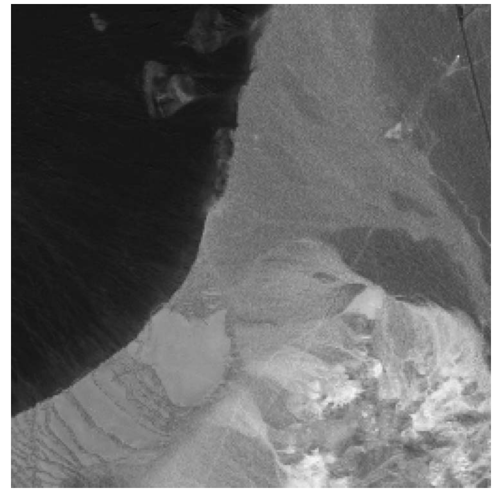

Fig. 3. Simulated Cuprite scene (spectral band #50).

The second test data cube is a simulated hyperspectral data cube that was created using the United States Geological Survey and portable infrared mineral analyzer laboratory spectra in combination with fraction (abundance) maps derived from AVIRIS data of Cuprite Nevada, USA. The data were resampled to have full width at half maximum values of 10 nm using a Gaussian weighted resampling kernel, processed to at-sensor radiance and 16-bit encoded. The test noisy data cube was formed by adding normally distributed zero mean noise with variance adjustments by band to achieve a nominal SNR of 600 : 1 obtained from the same source. The size of the data cube is 256 $\times$ 256 pixels with 213 bands. Fig. 3 shows band #50 of the simulated noise-free Cuprite data cube.

The SNR for hyperspectral data cubes is defined as

$$SNR = \frac{\sum\limits_{i,j,k} A(i,j,k)^2}{\sum\limits_{i,j,k} \left[B(i,j,k) - A(i,j,k)\right]^2} \tag{5}$$

where B is the test noisy data cube or the denoised data cube and A is the reference (noise free) data cube. Table I tabulates the SNRs of the denoisy data cube produced by the proposed method in this paper, the HSSNR method, the bivariate wavelet shrinkage, the VisuShrink method, and the Wiener filter, respectively. It can be seen that bivariate shrinkage, VisuShrink, and the Wiener filter have removed useful features during the denoising process. The SNRs produced by them are worse than that of the test data cube. Table II shows the factor of SNR improvement of the denoising methods. This indicates that the proposed method is better than the HSSNR method for denoising hyperspectral data cube.

For illustrative purposes, Fig. 4 shows the first 12 PCA output channels of the GVWD noisy data cube. It can be seen that the first $k = 8$ output channels contain fine features, while those output channels after contain significant amount

TABLE I
SNRs PRODUCED BY THE PROPOSED METHOD, THE HSSNR, THE BIVARIATE WAVELET SHRINKAGE, THE VISUSHRINK, AND THE WIENER FILTER

Datacube	Test noisy datacube	Proposed	HSSNR	Bivariate	VisuShrink	Wiener
GVWD	1811.26	**6206.18**	3621.97	416.59	46.76	934.06
Cuprite	5297.47	**13473.89**	9193.44	1873.01	342.57	4074.12

TABLE II
FACTOR OF SNR IMPROVEMENT OF THE PROPOSED METHOD IN THIS PAPER AND THE HSSNR METHOD, THE BIVARIATE WAVELET SHRINKAGE, THE VISUSHRINK, AND THE WIENER FILTER

Datacube	Test noisy datacube	Proposed	HSSNR	Bivariate	VisuShrink	Wiener
GVWD	1.0	**3.43**	2.00	0.23	0.02	0.52
Cuprite	1.0	**2.54**	1.74	0.35	0.06	0.77

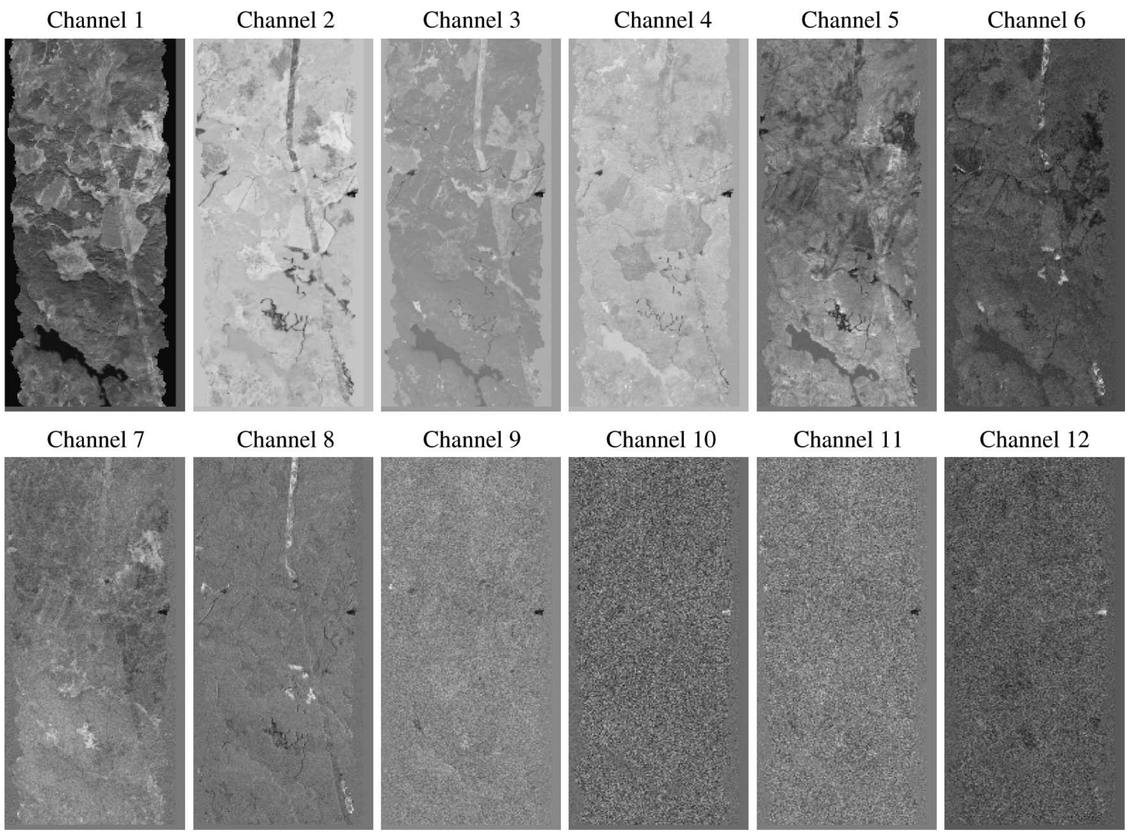

Fig. 4. PCA output channels (1–12) for the AVIRIS GVWD data cube.

of noise. Therefore, the proposed denoising method can be applied to the ninth channel until the last channel. Fig. 5 shows the first 12 PCA output channels of the Cuprite noisy data cube. It can be seen that the first $k = 3$ output channels contain fine features, while those output channels after have significant amount of noise. Therefore, the proposed denoising method can be applied to the fourth channel until the last channel of this data cube. Figs. 6 and 7 show a spectrum of an arbitrary pixel in the noise-free GVWD and the Cuprite data cubes, and the difference between the noise-free spectrum and the spectra obtained by different denoising methods. At this particular pixel, the proposed denoising method produces better or comparable difference spectrum when compared with other denoising methods discussed in this paper.

Hyperspectral data cubes contain a huge amount of data; thus, the neighborhood size is critical in denoising. If the neighborhood size is too large, the denoising will be extremely slow. This is a very important drawback. In this paper, we have chosen an intermediate window size of 7×7 for the bivariate wavelet denoising method (Table III).

We have also compared the proposed denoising method given in this paper with the same method without 1-D spectral denoising. Experimental results are shown in Table IV. From the table, it can be seen that the proposed method with spectral denoising is better than that without spectral denoising.

IV. CONCLUSION

In this paper, a new denoising method is proposed for hyperspectral imagery that carries very low-level band-varying noise. Since the noise level is very low in the data cube, the conventional image denoising methods will remove the fine

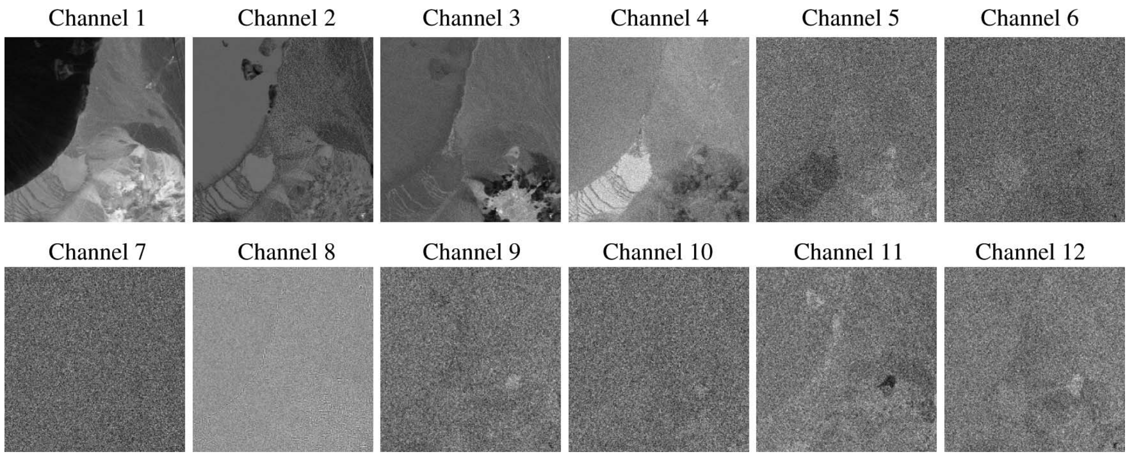

Fig. 5. PCA output channels (1–12) for the simulated Cuprite data cube.

TABLE III
SNR's PRODUCED BY USING DIFFERENT NEIGHBORHOOD SIZES IN THE BIVARIATE WAVELET SHRINKAGE

Datacube	3×3	5×5	7×7	9×9	11×11	13×13
GVWD	5599.23	5999.05	6206.18	6340.92	6446.79	6538.56
Cuprite	12944.65	13311.76	13473.89	13569.45	13640.73	13700.42

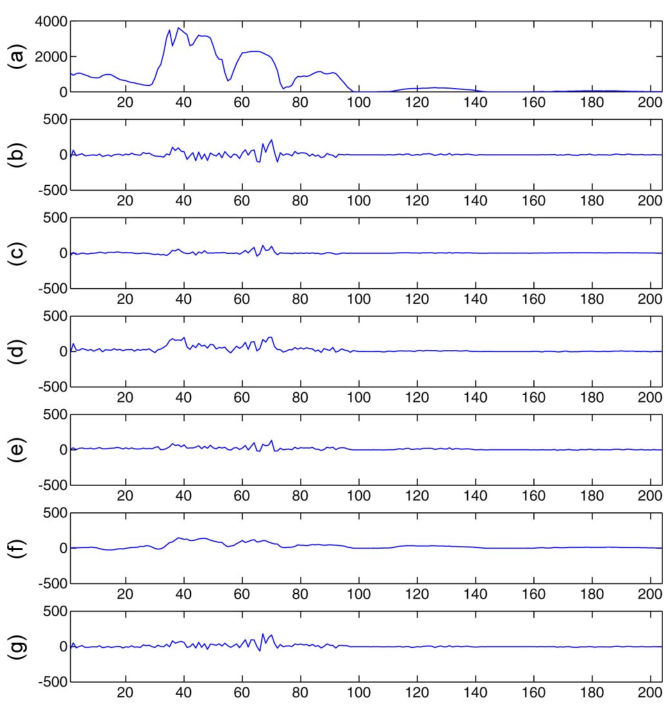

Fig. 6. (a) Spectrum of one of the pixels in the AVIRIS GVWD data cube, (b) the difference between the noise-free spectrum and the noisy spectrum, and (c) the difference between the noise-free spectrum and the spectra obtained by the proposed method, (d) HSSNR, (e) bivariate shrinkage, (f) VisuShrink, and (g) the Wiener filter.

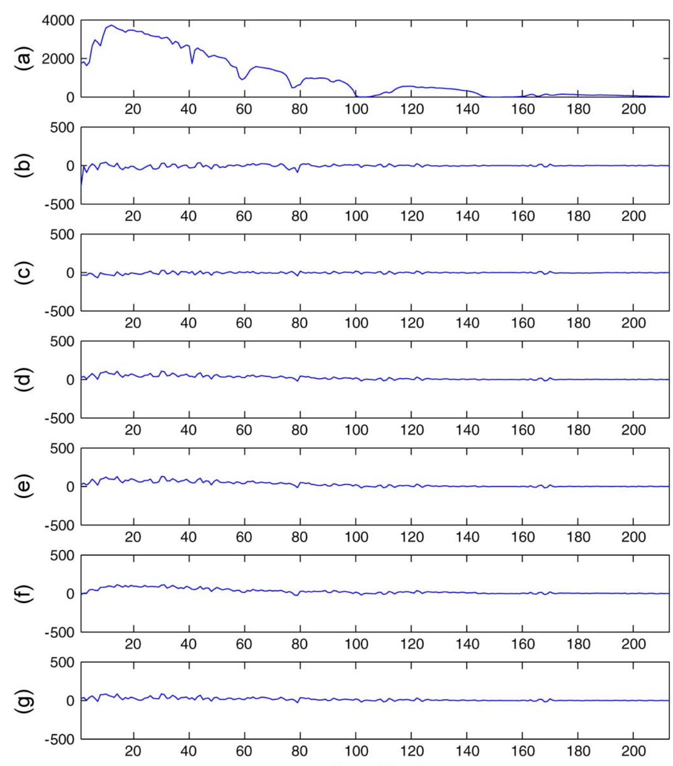

Fig. 7. (a) Spectrum of one of the pixels in the simulated Cuprite data cube, (b) the difference between the noise-free spectrum and the noisy spectrum, and (c) the difference between the noise-free spectrum and the spectra obtained by the proposed method, (d) HSSNR, (e) bivariate shrinkage, (f) VisuShrink, and (g) the Wiener filter.

features in the data cube during the denoising process. The proposed denoising method in this paper utilizes the PCA to decorrelate the fine features of the data cube from the noise, reducing the noise only in the noisy low-energy channels. A 2-D bivariate wavelet thresholding method is used to remove the noise for low-energy PCA channels, and a 1-D dual-tree complex wavelet transform denoising method is used to remove the noise of the spectrum of each pixel of the data cube.

Experimental results show that the proposed denoising method outperforms other denoising methods published in the literature.

TABLE IV
SNR's PRODUCED BY THE PROPOSED METHOD IN THIS PAPER AND THE BIVARIATE WAVELET SHRINKAGE WITHOUT 1-D SPECTRAL DENOISING

Datacube	Test noisy datacube	Proposed	Results without ID spectral denoising
GVWD	1811.26	**6206.18**	416.59
Cuprite	5297.47	**13473.89**	1873.01

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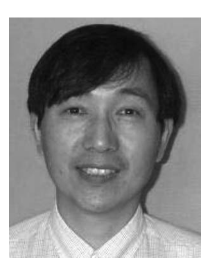

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