HYPERSPECTRAL IMAGE DEBLURRING WITH PCA AND TOTAL VARIATION

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ABSTRACT

In this paper, we propose a novel algorithm for hyper-spectral (HS) image deblurring with principal component analysis (PCA) and total variation (TV). We first decorrelate the HS images and separate the information content from the noise by means of PCA. Then, we employ the TV method to jointly denoise and deblur the first principal components (PCs). Subsequently, noise in the last principal components is suppressed using a simple soft-thresholding scheme, for computational efficiency. Experimental results on simulated and real HS images are very encouraging.

***Index Terms*—** Hyper-spectral images, deblurring, principal component analysis, total variation

1. INTRODUCTION

Despite advances in sensor technology, HS images are inevitably degraded by noise and blur, which can affect information retrieval and content interpretation. Using denoising and deblurring as a preprocessing tool will improve various post-processing tasks, e.g. classification, target detection, unmixing, etc.

Many techniques have been developed for denoising and deblurring of HS data [1, 2, 3, 4]. Li et al. [1] propose a TV-based coupled segmentation and deblurring model for HS material identification. Zhao et al. [2] present a model containing both TV and sparsity promoting terms to deal with deblurring and unmixing of HS data. Chen et al. [3] propose a HS image denoising algorithm using PCA and wavelet shrinkage. Their algorithm utilizes PCA to decorrelate the fine HS features from the noise, and then reduce the noise only in the low-energy PCA channels with wavelet shrinkage denoising. Zhang et al. [4] propose a multi-frame image super-resolution reconstruction algorithm for HS images in the PCA transform domain. Their algorithm divides all PCs into three groups, and only utilizes the first few PCs for both the motion estimation (between the HS image sequences) and super-resolution reconstruction processes.

This work was supported by the SBO-IWT project Chameleon: Domain-specific Hyperspectral Imaging Systems for Relevant Industrial Applications.

However, to the best of our knowledge, the HS deblurring method in PCA transform domain has not been investigated yet. In many real world applications, the high dimensionality of HS data as well as the redundancy (high correlation) between the bands, make the processing of HS images very computationally intensive. To overcome this problem, dimension reduction is firstly applied to the HS images, and then image restoration is applied to a few dimension-reduced HS bands. The effect of HS image processing based on dimension reduced HS bands has been discussed in several studies [4, 5].

In this paper, we propose a novel deblurring algorithm for HS images. Fig. 1 depicts an overview of the proposed method. Our method first uses PCA to decorrelate the HS images and separate the information content from the noise. The first k PCA channels contain most of the total energy of a HS image (i.e. most information of the HS image), and the remaining $B - k$ PCA channels (where B is the number of spectral bands of HSI and $B \gg k$) mainly contain noise. If deblurring is performed on these noisy and high-dimensional $B - k$ PCs, then it will amplify the noise of the data cube and cause high computational cost in processing the data, which is undesirable. Therefore, we use a fast TV method with group sparsity [7] to jointly denoise and deblur only the first k PCA channels. We remove the noise (without deblurring) in the remaining PCA channels using a soft-thresholding scheme. The results demonstrate effectiveness of the proposed method both visually and quantitatively.

2. PROPOSED METHOD

In this section, we develop a joint deblurring and denoising method for HS images. TV denoising and deblurring is widely used in image processing applications [1, 2, 4, 6, 8], because of its good edge preserving capabilities and also due to its computational efficiency, which is important when processing large data cubes. Suppose u_i is the reference band, f_i ($i \in \{1, \cdots, B\}$) the acquired bands of HS image, and H the linear blur operator. The most direct solution, for HS image deblurring, is to apply the following well-developed

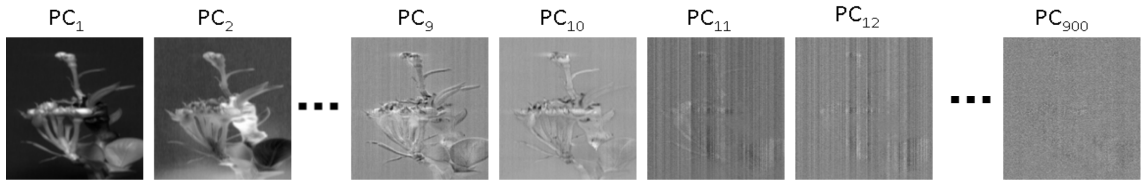


Fig. 2: Principal components of real HS image.

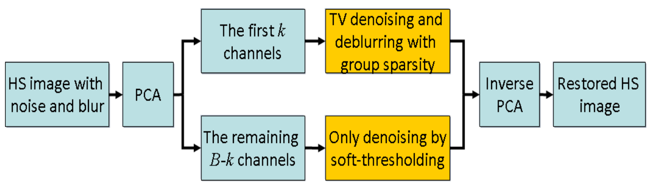


Fig. 1: Flow chart of the proposed deblurring method.

optimization problem to restore every separate spectral band individually:

$$\hat{u}_i = \arg\min_{u_i} |\nabla u_i| + \frac{\beta_i}{2}||Hu_i - f_i||_2^2 \tag{1}$$

where $\hat{u}_i$ is the estimated band of the u_i (the result of deblurring), ∇ the discrete gradient operator. The first term on the right side of (1) is the TV regularization, which is responsible for smoothing (i.e. noise reduction). The second term $||Hu_i - f_i||_2^2$ is commonly referred as data fidelity term. The parameter β_i controls the relative contribution of the data fidelity term and smoothing term. However, deblurring HS image band by band cannot fully exploit correlation across the spectral bands. Furthermore, both the parameter estimation of β and the image reconstruction for each band will cause high computational cost.

To overcome the problem, some approaches explore spectral information for HS restoration by combining 1D spectral denoising [3, 6]. In particular, we use the the group sparsity [7] to combine the spectral information. The group sparsity combines all the gradient coefficients of the different channels at the same spatial position into one group such that the resolving operator (soft-thresholding) does not act componentwise but treats the group as one vector:

$$\hat{u}_i = \arg\min_{u_i} \sum_{j=1}^{B} ||\nabla u_j||_2 + \frac{\beta}{2}||Hu_i - f_i||_2^2 \tag{2}$$

where $||\nabla u_i||_2$ is the TV group sparsity regularization. However, in real HS images, different bands suffer different level of noise, using the same parameter β in all bands (similar approaches [6] as group sparsity here) will lead to some artifacts in the resulting restoration HS image. Moreover, these similar optimization problems (like (2)) will cause high memory and computational cost in image reconstruction, particularly for HS images with a large number of bands.

Some approaches first apply PCA to decorrelate the HS images, and then perform image restoration in PCA transform domain [3, 4]. After the PCA transform, the signal components are decorrelated, we can solve the optimization problem of (1) in PCA transform domain band by band:

$$\hat{u}_i^{PC} = \arg\min_{u_i^{PC}} |\nabla u_i^{PC}| + \frac{\beta_i}{2}||Hu_i^{PC} - f_i^{PC}||_2^2 \tag{3}$$

However, similarly to (1), the optimization problem of (3) will cause high computational cost both due to the parameter (β_i) estimation and due to the image reconstruction.

In fact, the signal components are decorrelated after the PCA transform, and the energy contained in the HS image is maximally concentrated in a small number of components. Fig. 2 illustrates PCA transform on a HS image with 900 spectral bands. We note that most of the information is concentrated in the first 10 PCs, while the remaining 890 PCs in the second part contain a large amount of noise with much less information. If deblurring is performed on these remaining PCs based on the optimization problem (3), the parameter β_i ($i \in \{k+1, \cdots, B\}$) should be set to a very small value, which is approximately TV denoising problem (the H in (3) is set to an identity operation). That is why we propose an implementation as a denoising problem (5), to avoid noise enhancement due to inaccurate parameter choice.

Therefore, we propose a novel algorithm to approximately solve the optimization problem of (3). We first divide all the PCs into two groups according to the information content they contain. Then, denoising and deblurring are only performed on the first k PCs through the minmizations:

$$\hat{u}_i^{PC} = \arg\min_{u_i^{PC}} \sum_{j=1}^{k} ||\nabla u_j^{PC}||_2 + \frac{\lambda_1}{2}||Hu_i^{PC} - f_i^{PC}||_2^2 \tag{4}$$

and denoising is only conducted on the remaining $B-k$ PCs (we call this method PCA$_{TVTV}$ in the following) through the following estimation:

$$\hat{u}_i^{PC} = \arg\min_{u_i^{PC}} \sum_{j=k+1}^{B} ||\nabla u_j^{PC}||_2 + \frac{\lambda_2}{2}||u_i^{PC} - f_i^{PC}||_2^2 \tag{5}$$

However, when dealing with these large data cubes in real-time, solving the optimization problem (5) will require a high memory and computational cost. Therefore, we only apply 2D (band by band) wavelet soft-thresholding denoising to remove the noise in these remaining PCs due to its efficiency and effectiveness (we call it PCA$_{TVST}$). In our implementation, (2), (4) and (5) are solved by a very fast and memory efficient first-order primal-dual algorithm [8].

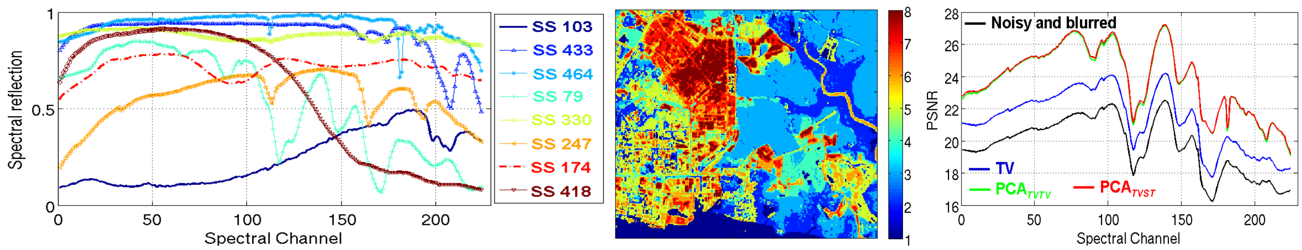


Fig. 3: Left: the spectral signatures (SS) of eight materials; middle: the thematic map; right: the PSNR per spectral band. The colors of the spectral signatures correspond to the colors of the thematic map.

3. EXPERIMENTAL RESULTS

To assess the quantitative performance of the proposed HS deblurring method, we perform an experiment involving a synthetic HS image. The synthetic HS image is generated in the following way: first, a remote sensing thematic map corresponding to landcover types from the National University of Singapore[1] is used. Second, eight spectral signatures[2] (laboratory measured absolute reflectances) are randomly selected from the UCGS digital library [9]. In particular, the thematic map with the size of 278×329 has eight classes (labeled with different color in Fig. 3). The USGS digital library [9] contains 501 spectral signatures with 224 spectral bands. We then associate different colors of spectral signatures to the eight corresponding colors of regions in the thematic map, resulting in a $278 \times 329 \times 224$ (spatial $\times$ spatial $\times$ spectral) HS image. The simulated HSI is blurred spatially with a Gaussian point spread function (with $\sigma = 1$), and then degraded by white Gaussian noise of SNR 30 dB. We compare the Peak Signal-to-Noise Ratio (PSNR) of each spectral band (Fig. 3 (right)) among TV (TV deblurring with group sparsity on original HS image), and our proposed method PCA$_{TVTV}$ (first using PCA to decorrelate the HS image, then TV deblurring with group sparsity on first k PCs and only TV denoising on the remaining $B-k$ PCs) and PCA$_{TVST}$ (the same as PCA$_{TVTV}$ for the first k PCs, but differing in only denoising the remaining $B-k$ PCs by 2D soft-thresholding). The PSNR is computed by PSNR $= 10log10(MAX_i^2/MSE)$, where MAX_i is the maximal intensity of the HS band (if 16-bit hyperspectral data then $MAX_i = 2^{16}-1$), and where the mean squared error (MSE) is directly computed based on the processed HS band and the original (ideal) image. We do not compare the results of deblurring band by band because of its high computational cost in estimating the parameter β_i. The parameters β and λ_1 are automatically optimized according to the average PSNR of all bands using cross-validation within big range in the given set $\{2^{-8}, 2^{-6}, \cdots, 2^6, 2^8\}$, the parameter λ_2 in (5) is set to 10^{-10}.

It is clear that our proposed method (PCA$_{TVTV}$ and PCA$_{TVST}$) provides a higher PSNR (around 2dB) than when deblurring is directly performed on the original HS image. This is due to the noisy and blurred information in most bands, and the strong correlation between the spectral bands. After the PCA transform, the HS image is decorrelated and most information is concentrated in the first k PCs. The remaining $B-k$ PCs mainly contain the noise, which is efficiently removed by only denoising.

To further verify the effectiveness of our proposed approach, we applied the deblurring methods to the real HS image with size of $1392 \times 731 \times 1040$ (spatial $\times$ spatial $\times$ spectral) pixels, which was captured by the department of Biosystems from KU Leuven with a rotary hyperspectral measuring setup (with wavelength range from 321nm to 995 nm and spatial resolution of approximately 0.5 mm). The application here is detecting and counting the floral pear buds [10]. In our experiments, we select a sub-image with size of $400 \times 350 \times 900$ (spatial $\times$ spatial $\times$ spectral) pixels by cropping the hyperspectral datacube, which corresponds to wavelength range from 411nm to 995 nm (after removing noise). Fig. 4 shows some deblurred bands. We assume the real data is blurred spatially with Gaussian point spread function ($\sigma = 2$) and we select the parameter β empirically from visual inspection. Alternatively, this can also be done by blur estimation [11].

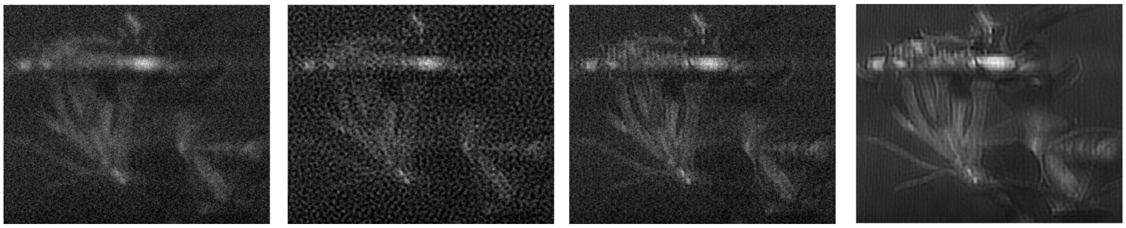
The experiments (in Matlab 2012b) are carried out on 64-bit, Intel Core i7-3930K @ 3.20GHz (6 core) CPU computer with 32 GB memory. The elapsed times for TV, PCA$_{TVTV}$ and PCA$_{TVST}$ are 342.4 seconds, 184.9 seconds and 43.7 seconds, respectively. When applying TV denoising and deblurring to the original HS image, the noise in some noisy bands is amplified, see band 1 and band 900 in Fig. 4. Our proposed method (PCA$_{TVTV}$ and PCA$_{TVST}$) reconstructs the HS image better than TV, with less remaining noise and more detail information. Furthermore, the proposed method (especially the PCA$_{TVST}$) is much faster.

4. CONCLUSION

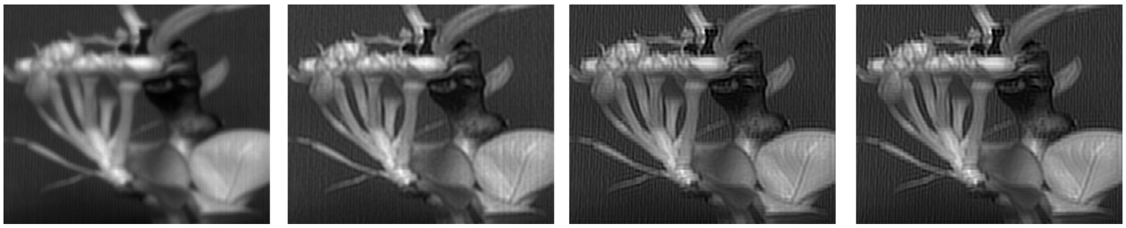
A novel deblurring method for hyperspectral images is proposed in this paper. We first use a PCA transform to decorrelate the HS image and to separate the information content

[1] http://www.crisp.nus.edu.sg/~research/tutorial/xsc8.gif.

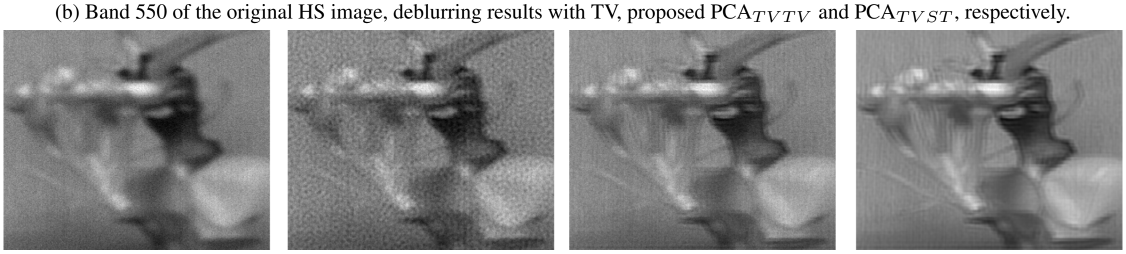
[2] For the sake of reproducible research, we mention the exact index (and name) of the signatures from this database, these are signature number (and name) 79 (Carnallite HS430.3B), 103 (Clinochlore_Fe SC-CCa-1.a), 174 (Grossular WS484), 247 (Kaolin/Smect H89-FR-5 30K), 330 (Oligoclase HS143.3B), 418 (Sodium_Bicarbonate GDS55), 433 (Strontianite HS272.3B) and 464 (Topaz Glen_Cove_#8).



(a) Band 1 of the original HS image, deblurring results with TV, proposed PCA_{TVTV} and PCA_{TVST}, respectively.



(b) Band 550 of the original HS image, deblurring results with TV, proposed PCA_{TVTV} and PCA_{TVST}, respectively.



(c) Band 900 of the original HS image, deblurring results with TV, proposed PCA_{TVTV} and PCA_{TVST}, respectively.

Fig. 4: Part of the deblurring result on the real hyperspectral data.

from the noise. We then employ a fast TV method with group sparsity to denoise and deblur only the first k PCs, and a soft-thresholding denoising scheme to only remove noise in the remaining $B-k$ PCs. Experimental results on simulated and real HS images show the efficiency of the proposed method. Our future work will perform classification experiments (e.g. flower bud detection, target detection in remote sensing) to further validate the proposed method.

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