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Hyperspectral image recovery employing a multidimensional nonlocal total variation model

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ABSTRACT

Hyperspectral images (HSIs) have a high spectral resolution and ground-object recognition ability, but inevitably suffer from various factors in the imaging procedure, such as atmospheric effects, secondary illumination, and the physical limitations, which have a direct bearing on the visual quality of the images and the accuracy of the subsequent processing. HSI restoration is therefore a crucial task for improving the precision of the subsequent products. Currently, patch-based schemes have offered promising results for the preservation of detailed information and the removal of additive noise. In HSIs, the information in the spectral dimension is more redundant than the information in the spatial dimension. We therefore propose a multidimensional hyperspectral nonlocal model, in which both the correlation of the spectral bands and the similarity of the spatial structure are considered. In the model, a multidimensional nonlocal total variation constraint is applied to preserve edge sharpness. Experiments with both synthetic and real hyperspectral data illustrate that the proposed method can obtain promising results in HSI restoration.

1. Introduction

Hyperspectral images (HSIs) simultaneously provide spatial and spectral information to identify specific materials in a scene. Unfortunately, during the acquisition procedure of HSIs, atmospheric effects, secondary illumination, and the physical limitations of the sensors (such as artifacts, sensor noise, and dead pixels) degrade the quality of the images [1]. These disturbance factors influence the visual effect of the HSIs and limit the precision of the subsequent applications, such as land-surface classification, object identification, and change detection. To achieve a more accurate estimation, it is important to overcome these limitations and improve the quality of the HSIs.

HSI restoration aims at generating a high-quality image from its degraded version. To date, various HSI restoration techniques have been proposed. We review the existing popular HSI restoration methods in the following. One type of methods is based on the strategy of transform domain [2–6]. With these methods, the input hyperspectral signals are converted into signals in another space, such as the wavelet domain, in which the noise is easily separated from the signal using the compactness of the true signal. The traditional wavelet denoising techniques apply a 2D wavelet transform on each band separately, and thus discard the spectral correlation information. To improve its performance with HSIs, the wavelet transform has been combined with other spectral band decorrelation methods, such as

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discrete Fourier transform [2] and PCA [3,4]. To exploit the inter-band correlation and spatial information, other advanced HSI noise reduction techniques can be accomplished through wavelet thresholding [5] in the Bayesian estimation framework, and in combination with different prior models [7–10]. However, the biggest drawback of the wavelet-based methods is that they often generate ringing artifacts, shown as additional edges or structures [11].

To preserve the spectral feature, multidimensional filter methods [12–14] have been developed to consider the HSI as a multidimensional data cube in the spatial domain, to simultaneously process the spatial and spectral information. These methods include the multidimensional Wiener filter [12], genetic kernel tucker decomposition [15], and adaptive 3D filtering [16]. However, the classical multidimensional analysis methods can have great difficulty in distinguishing the signal and noise subspaces, and thus may introduce some artifacts, and they also tend to oversmooth the image and lose many textural details [13].

Together with the progress made in remote sensing, to better preserve the textural details and overcome the artifacts, regularization-based approaches [17–23] have emerged in recent years to enhance both the spatial structure and spectral feature. These approaches recover the original image by adding a reasonable assumption or prior knowledge into the observation model. The different priors can be applied to meet different goals, such as preserving edges, protecting textural details, and avoiding artifacts and noise. Yuan et al. [18] employed a spectral–spatial adaptive total variation (TV) model to adaptively denoise image in both the spatial and spectral dimension. Chen and Hu [19] proposed a spatial–spectral domain mixing prior, in which an edge-preserving prior is used to preserve the geometrical structure in the spatial domain, and adaptive spectral weights for the different materials are constructed in the spectral domain. Qian [20] used variance-stabilizing transformation to simplify the mixed-noise into Gaussian noise, and then introduced a structured sparsity-based model to remove the noise.

In regularization-based algorithms, the HSI recovery is cast as the inverse problem of recovering the original high-quality image. A robust estimation for the solution is obtained relying on some strong image priors, and various regularization functions have been proposed to further stabilize the inversion of this ill-posed problem, such as Tikhonov regularization [24], Gaussian Markov random fields regularization [25], Huber-MRF regularization [26], TV regularization [18], nonlocal-based regularization [27,28], and sparse regularization [21,22]. Among these models, the nonlocal-based model [29] is a very popular and powerful tool, which has been widely used in various applications, such as denoising [30], super-resolution reconstruction [31], inpainting [32], and shadow removal [33], because of its good performance in edge and texture preservation.

For HSIs, the simplest way to apply a nonlocal-based regularization is in a band-by-band manner. However, the spectral dependency and inter-channel relationship of the hyperspectral signals will not be fully made use of. Furthermore, owing to the relatively low spatial resolution of HSI [34], the similarity between patches from only a single band is insufficient. At the same time, as the noise-intensity in each band is usually different, the denoising strength should be adaptively adjusted with the noise-intensity in each band. Therefore, we propose a spectrally adaptive multidimensional nonlocal total variation (SAMNLTV) model by exploiting the high correlation of bands to better restore a low-quality HSI. The main ideas and contributions of the proposed approach can be summarized as follows:

(1) A multidimensional nonlocal TV regularization is proposed to acquire more redundancy from the highly correlated bands. Since the intensity of the signal is contiguous in the highly correlated or neighboring bands, they are selected to provide more similar patches in the scheme.
(2) A spectrally adaptive method is proposed for the multidimensional nonlocal TV model. To suppress the different intensities of noise in the different bands, a wavelet method is applied to roughly estimate the strength of noise in the different bands. By making use of the noise strength, an adaptive regularization parameter selection strategy is proposed to improve the restoration results.
(3) A split Bregman iteration algorithm is used to optimize the proposed HSI restoration model. From the experimental results with both simulated and real data, it is illustrated that the proposed model produces good image restoration results.

The rest of this paper is organized as follows. In Section 2, the proposed multidimensional nonlocal total variation model is formulated. Section 3 contains the experimental results and discussion, and Section 4 is the conclusion.

2. The multidimensional nonlocal total variation model

Assuming that we have a HSI $\mathbf{U} \in \mathrm{R}^{M_1M_2\times B}$ corrupted by an additive noise $\mathbf{V} \in \mathrm{R}^{M_1M_2\times B}$. Mathematically, this is denoted as $\mathbf{U} \in \mathrm{R}^{M_1M_2\times B}$, where the matrix representation of the original HSI is of a size of $M_1 \times M_2 \times B$, in which M_1 represents the number of samples in a line, M_2 stands for the number of lines in the image, and B denotes the number of bands. The degradation model for each band can then be defined as

$$\boldsymbol{f}_b = \boldsymbol{u}_b + \boldsymbol{v}_b \tag{1}$$

where $\mathbf{u}_b \in \mathrm{R}^{M_1M_2}$ denotes the vector representation of one band with a size of $M_1 \times M_2$. $\mathbf{f}_b \in \mathrm{R}^{M_1M_2}$ denotes one band of the degraded image $\boldsymbol{F} \in \mathrm{R}^{M_1M_2\times B}$, and the additive noise is $\mathbf{v}_b \in \mathrm{R}^{M_1M_2}$, which is added to the bands $\mathbf{u}_b$.

Applying the maximum a posteriori probability (MAP) estimator, the HSI restoration model can be represented as the following regularized least squares problem [18]:

$$\widehat{\boldsymbol{U}} = \arg\min_{\mathbf{U}} \left\{ \sum_{b=1}^{B} \|\boldsymbol{u}_b - \mathbf{f}_b\|_2^2 + \lambda \Phi(\boldsymbol{U}) \right\} \tag{2}$$

In the cost function, the first term is called the fidelity term, which denotes the fidelity between the observed noisy data and the original clear data, while the second term $\Phi(\boldsymbol{U})$ is an additional regularization function. λ is the regularization parameter used to balance the tradeoff between the fidelity term and the regularization term.