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Denoising Of Hyperspectral Image

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ABSTRACT
The amount of noise included in a Hyperspectral images limits its application and has a negative impact on Hyperspectral image classification, unmixing, target detection, so on. Hyperspectral imaging (HSI) systems can acquire both spectral and spatial information of ground surface simultaneously and have been used in a variety of applications such as object detection, material identification, land cover classification etc.
In Hyperspectral images, because the noise intensity in different bands is different, to better suppress the noise in the high noise intensity bands & preserve the detailed information in the low noise intensity bands, the denoising strength should be adaptively adjusted with noise intensity in different bands. We propose a Hyperspectral image denoising algorithms employing a spectral spatial adaptive total variation (TV) model, in which the spectral noise difference & spatial information differences are both considered in the process of noise reduction.
To reduce the computational load in the denoising process, the split Bergman iteration algorithm is employed to optimize the spectral spatial Hyperspectral TV model and accelerate the speed of Hyperspectral image denoising. A number of experiments illustrate that the proposed approach can satisfactorily realize the spectral spatial adaptive mechanism in the denoising process, and superior denoising result are provided.
Keywords – Hyperspetral images denoising, spaital adaptive, spectral adaptive, spectral spatial adaptive Hyperspectral total variation, split Bregman iteration.

I. INTRODUCTION

Hyperspectral image (HIS) analysis has matured into one of most powerful and fastest growing technologies in the field of remote sensing. A Hyperspectral remote sensing system is designed to faithfully represent the whole imaging process on the premise of reduced description complexity. It can help system users understand the Hyperspectral imaging (HSI) system better and find the key contributors to system performance so as to design more advanced Hyperspectral sensors and to optimize system parameters. A great number of efficient and cost-effective data can also be produced for validation of Hyperspectral data processing. As both sensor and processing systems become increasingly complex, the need for understanding the impact of various system parameters on performance also increases.

Hyperspectral images contain a wealth of data, interpreting them requires an understanding of exactly what properties of ground materials we are trying to measure, and how they relate to the measurements actually made by the Hyperspectral sensor.

The Hyperspectral data provide contiguous of noncontiguous 10-nm bands throughout the 400-2500-nm region of electromagnetic spectrum and, hence have potential to precisely discriminate different land cover type using the abundant spectral information.such identification is of great significance for detecting minerals,precision farming urban planning, etc

The existence of noise in a Hyperspectral image not only influences the visual effect of these images but also limits the precision of subsequent processing, for example, in classification, unmixing subpixel mapping, target detection, etc. Therefore, it is critical to reduce the noise in the Hyperspectral image and improve its quality before the subsequent image interpretation processes. In recent decades, many Hyperspectral image denoising algorithms have been proposed. For example, Atkinson [6] proposed a wavelet-based Hyperspectral image denoising algorithm, and Othman and Qian [7] proposed a hybrid spatial–spectral derivative-domain wavelet shrinkage noise reduction (HSSNR) approach. The latter 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 the spectral dimensions of Hyperspectral images. Chen and Qian [8], [9] proposed to perform dimension reduction and Hyperspectral image denoising using wavelet shrinking and principal component analysis (PCA).
Qian and Lévesque [10] evaluated the HSSNR algorithm on unmixing-based Hyperspectral image

target detection. Recently, Chen [11] proposed a new Hyperspectral image denoising algorithm by adding a PCA transform before using wavelet shrinkage; first, a PCA transform was implemented on the original Hyperspectral image, and then, the low-energy PCA output channel was de-noised with wavelet shrinkage denoising processes. Another type of filter-based Hyperspectral image denoising algorithm is based on a tensor model, which was proposed by Letexier and Bourennane [12], and has been evaluated in Hyperspectral image target detection [13] and classification [14].Recently, afilter-based Hyperspectral image denoising approach using anisotropic diffusion has also been proposed [15]–[17].As Hyperspectral images have dozens or even hundreds of bands, and the noise intensity in each band is different, the denoising strength should be adaptively adjusted with the noise intensity in each band. In another respect, with the improvements in sensor technology, the development and increasing use of images with both high spatial and spectral resolutions have received more attention.

II. 2. METHOD OF IMPLEMENTATION

2.1 MAP Hyperspectral Image Denoising Model

2.1.1 Hyperspectral Noise Degradation Model.

Assuming that we have an original Hyperspectral image, and the degradation noise is assumed to be additive noise, the noise degradation model of the Hyperspectral image can be written as

$$f = u + n \qquad (1)$$

where $u = [u_1, u_2, \dots \dots u_{j \dots\dots}, u_B]$ is the original clear Hyperspectral image, with the size of M × N × B, in which M represents the samples of the image, N stands for the lines of the image, and B is the number of bands. $f = [f_1, f_2, \dots \dots f_{j \dots\dots}, f_B]$ The noise degradation image which also of size M × N × B, and $n = [n_1, n_2, \dots \dots n_{j \dots\dots}, n_B]$ is the additive noise with the same size as u and f. The degradation process Hyperspectral image is shown in "Fig.1".

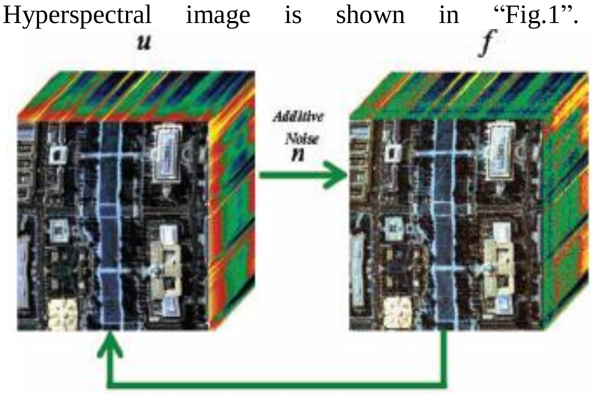

Fig. 1. Noise degradation process of the Hyperspectral image.

2.1.2 MAP Denoising Model

The MAP estimation theory, which inherently includes prior constraints in the form of prior probability density functions, has been attracting attention and enjoying Increasing popularity. It has been used to solve many image processing problems, which can be formed as ill-posed and inverse problems, such as image denoising, destriping and Inpainting, super resolution reconstruction, and others. Therefore, because the Hyperspectral image denoising process is an inverse and ill-posed problem. The MAP estimation theory is used to solve it. Based on the MAP estimation theory, the denoising model for a Hyperspectral image can be represented as the following constrained least squares problem

$$\hat{u} = \operatorname{argmin}\left\{\sum_{j=1}^{B} \| u_j - f_j \| \frac{2}{2} + \lambda R(u)\right\} \qquad (2)$$

$\sum_{j=1}^{B} \| u_j - f_j \| \frac{2}{2}$ Which stands for the fidelity between the observed noisy image and the original clear image, and R (u) is the regularization item, which gives a prior model of the original clear Hyperspectral image λ is the regularization parameter, which controls the tradeoff between the data fidelity and regularization item.

2.2 SSAHTV MODEL

2.2.1 TV Model

The TV model was first proposed by Rudin to solve the gray-level image denoising problem because of its property of effectively preserving edge information. For a gray-level image u, the TV model is defined as follows:

$$TV(u) = \sum_t \sqrt{\left(\nabla_i^h u\right)^2 + (\nabla_i^v u)^2} \qquad (3)$$

Where $\nabla_i^h$and $\nabla_i^v$are linear operators corresponding to the horizontal and vertical first-Differences respectively at pixel i.

Where $\nabla_i^h u = u_i - u_{b(i)}$

$u_i - u_{b(i)}$

r(i) and b(i) represent the nearest neighbor to the right and below the pixel.

2.2.2Spectral Adaptive Hyperspectral model

The simplest way of extending the TV model to Hyperspectral images is by a band-by-band manner, which means that, for every band, the TV model is defined like the gray-level image TV model in (3), and then, the TV model of each band is added together. This simple band-by-band Hyperspectral TV model is defined as follow

$$HTV(u)_1 = \sum_{j=1}^{B} TV(u_j) \qquad (4)$$

Where u is the Hyperspectral image, which has the formation of $u = u_1, u_2, \dots \dots u_{j \dots\dots}, u_B]$ and u_j stands for the j^{th} band of the Hyperspectral image. If we incorporate the band-by-band. For (5), the Euler–Lagrange equation is written as band Hyperspectral TV model in (5) into the Regularization model in (2), the denoising model can

$$\hat{u} = \operatorname{argmin}\left\{\sum_{j=1}^{B} \| u_j - f_j \|_2^2 + \lambda \sum_{j=1}^{B} TV(u_j)\right\} \quad (5)$$

Where

$$(u_j - f_i) - \lambda \nabla . \frac{\nabla u_j}{|\nabla u_j|} = 0. \quad (6)$$

From (6), it means that every band is separately denoised by the single-band TV model, which will cause the following drawback. For a Hyperspectral image, because the noise intensity of each band is almost always different, the denoising strength should also be different in each band. However, in (6), if we use the same regularization parameter λ for all the bands, which means that the regularization strength of each band is equal, to define the Hyperspectral TV model, which has the following formation:

$$HTV(u)_2 = \sum_{j=1}^{MN} \sqrt{\sum_{j=1}^{B} (\nabla_{ij} u_j)^2} \quad (7)$$

$$(\nabla_{ij} u_j)^2 = (\nabla_{ij}^{h} u)^2 + (\nabla_{ij}^{v} u)^2 \quad (8)$$

Where MN is the total number of pixels in one Hyperspectral band and B is the total number of bands. ∇_{ij}^{h} and ∇_{ij}^{v} are linear operators corresponding to the horizontal and vertical first order differences at the i^{th} pixel in the j^{th} band, respectively. To more clearly explain the formation of the Hyperspectral TV model, we use "Fig. 2" to illustrate it. The reason why the Hyperspectral TV model defined in (7) can realize the spectral adaptive property in the denoising process can be explained as follows. If we incorporate the Hyperspectral TV model in (7) into (2), it will become

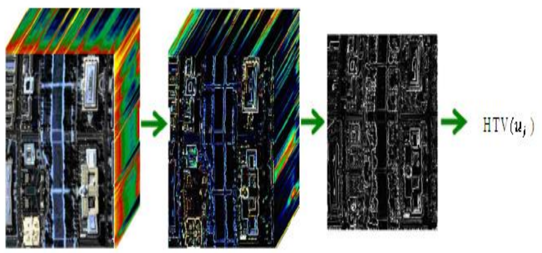

Fig.2 Formulation process of the Hyperspectral TV model.

$$\hat{u} = \operatorname{argmin}\left\{\sum_{j=1}^{B} \| u_j - f_j \|_2^2 + \lambda \sum_{i=1}^{MN} \sqrt{\sum_{j=1}^{B} (\nabla_{ij} u)^2}\right\} \quad (9)$$

In (9), if we take the derivative for uj, the Euler–Lagrange equation of (9) can be written as

$$(u_j - f_i) - \lambda \nabla . \frac{|\nabla uj|}{\sqrt{\sum_{j=1}^{B} (\nabla u_j) 2}} = 0 \quad (10)$$

To give a clearer illustration, (10) is written the following way:

$$(u_j - f_i) - \lambda \nabla . \frac{|\nabla uj|}{\sqrt{\sum_{j=1}^{B} |\nabla uj| 2}} . \frac{\nabla uj}{|\nabla uj|} = 0 \quad (11)$$

Compared with (6), we can see that an adjustment parameter $|\nabla uj| / \sqrt{\sum_{j=1}^{B} |\nabla u_j|^2}$ is added in (11) to automatically adjust the denoising strength of each band. For the high noise-intensity bands, as $|\nabla uj| / \sqrt{\sum_{j=1}^{B} |\nabla u_j|^2}$ has a large value, the denoising strength for these bands will be powerful. Inversely, for the bands with low-intensity noise, as $|\nabla uj| / \sqrt{\sum_{j=1}^{B} |\nabla u_j|^2}$ has a small value, a weak denoising strength will be used on them.

2.2.3 SSAHTV model

Spectral adaptive property of the Hyperspectral TV model is analyzed, another important problem is how to realize the spatial adaptive aspect in the process of denoising, which means how to adjust the denoising strength in different pixel locations in the same band, with the spatial structure distribution. The spatially adaptive mechanism can be described as follows. For a Hyperspectral image u, we first calculate the gradient information of every band using the following:

$$\nabla u_j = \sqrt{(\nabla^h u_j)^2 + (\nabla^v u_j)^2} \quad (12)$$

Where $\nabla^h u_j$ and $\nabla^v u_j$ are the horizontal and vertical first order gradients of u_j and $(\nabla^h u_j)$ 2 and $(\nabla^v u_j)$2 represent the squares of each element of $\nabla^h u_j$ and $\nabla^v u_j$. Next, the gradient information of every band is added together, and the square root is taken o f each element of the sum

$$G = \sqrt{\sum_{j=1}^{B} (\nabla u_j)^2} \quad (13)$$

Let G_i be the i^{th} element of vector G, and a weight parameter W_i , which controls the interband denoising strength, is defined in the following:

$$T_i = \frac{1}{1+\mu G_i} \quad (14)$$

$$W_i = \frac{T_i}{\overline{\overline{T}}} \quad \overline{T} = \frac{\sum_{i=1}^{MN} T_i}{MN} \quad (15)$$

Where μ is a constant parameter, the range of parameter τ is between [0, 1], and τ is the mean value of T_i . To make the process of denoising spatially adaptive, the parameter W_i is added to the Hyperspectral TV model in (7), and the SSAHTV model is defined as

$$SSAHTV(u) = \sum_{i=1}^{MN} W_i \sqrt{\sum_{j=1}^{B} (\nabla_{ij} u)^2} \quad (16)$$

Where W_i represents the spatial weight of the i^{th}

pixel in the Hyperspectral TV model. With the definition in (16), it is clearly seen that, for pixels in smooth regions, the value of the gradient information W_i will be small and the spatial weight W_i will have a high value. Therefore, a powerful denoising strength will be used for these pixels, and the noise in the smooth areas will be suppressed better. Conversely, for the pixels in the edge and texture areas. The value of G_i will be large, and the spatial parameter W_i will have a small value. Thus, a weak denoising strength will be used for them, and the edge and detailed information will be preserved. With the SSAHTV model, the final MAP denoising model used can be written as

$$\hat{u} = \operatorname{argmin} \left\{ \sum_{j=1}^{B} \| u_j - f_j \|_2^2 + \lambda \sum_{i=1}^{MN} W_i \sqrt{\sum_{j=1}^{B} (\nabla_{ij} u)^2} \right\} \quad (17)$$

III. Conclusion

Spectral Spatial Adaptive TV Hyperspectral image denoising algorithm, in which the noise distribution difference between different bands and the spatial information difference between different pixels are both considered in the process of denoising. First, a MAP-based Hyperspectral denoising model is constructed, which consists of two items:1) The data fidelity item and 2) The regularization item. Then, for the regularization item, an SSAHTV model is proposed, which can control the denoising strength between different bands and pixels with different spatial properties. In different bands, a large denoising strength is enforced in a band with high noise intensity, and conversely, a small denoising strength is used in bands with low-intensity noise. At the same time, in different spatial property regions in the Hyperspectral image, a large denoising strength is used in smooth areas to completely suppress noise, and a small denoising strength is used in the edge areas to preserve detailed information. Finally, the split Bergman iteration algorithm is used to optimize the spectral–spatial adaptive TV Hyperspectral image denoising model in order to reduce the high computation load in the process of Hyperspectral image denoising.

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