ARTICLE IN PRESS
JID: NEUCOM [m5G;May 23, 2017;19:19]
Neurocomputing 000 (2017) 1–12
Contents lists available at ScienceDirect
Neurocomputing
journal homepage: www.elsevier.com/locate/neucom

Group sparsity based regularization model for remote sensing image stripe noise removal

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ARTICLE INFO

Article history:
Received 23 December 2016
Revised 18 March 2017
Accepted 1 May 2017
Available online xxx

Communicated by Dr. Y Gu

Keywords:
Convex optimization
Group sparsity
Alternating direction method of multipliers
Remote sensing image
Image destriping

ABSTRACT

Stripe noise degradation is a common phenomenon in remote sensing image, which largely affects the visual quality and brings great difficulty for subsequent processing. In contrast to existing stripe noise removal (destriping) models in which the reconstruction is performed to directly estimate the clean image from the striped one, the proposed model achieves the destriping by estimating the stripe component firstly. Since the stripe component possesses column sparse structure, the group sparsity is employed in this study. In addition, difference-based constraints are used to describe the direction information of the stripes. Then, we build a novel convex optimization model which consists of a unidirectional total variation term, a group sparsity term and a gradient domain fidelity term solved by an efficient alternating direction method of multiplier. Compared with the state-of-the-art methods, experiment results on simulated and real data are reported to demonstrate the effectiveness of the proposed method.

1. Introduction

Remote sensing image plays an important role in many fields, such as urban planning, military, and environment monitoring. However, different sensors produce inconsistent responses in the imaging process, which leads to the images degraded by stripe noise. The stripe noise existing in remote sensing image badly degrades the visual quality and restricts the precision in data analysis, such as unmixing [1], classification [2], and target detection [3]. To reduce the unfavorable effects caused by stripe noise, it is critical to develop efficient methods to remove the stripes before subsequent applications. The goal of this work is to separate the stripe component and preserve the stripe-free information.

In recent decades, a lot of destriping methods have been proposed. Extensively existing destriping methods can be roughly divided into three categories: digit filtering-based methods, statistics-based methods, and optimization-based methods. It is worth mentioning that these methods sometimes have overlap among this categories. For instance, some optimization-based methods may involve statistics-based methodological ideas.

One straightforward idea for image destriping is filtering. These filtering-based methods remove stripes by constructing a filter on a transformed domain, e.g., Fourier domain filter [4–6], wavelet analysis [7,8] and the Fourier-wavelet combined domain filter [9,10]. These methods suppose that the stripes are periodic and can be clearly discovered from the power spectrum. However, some evident details with the similar features to the stripes also exist in the stripe-free regions, these details would be excessively filtered out, which results in blurring or artifacts of the output image. In [9], the authors proposed Fourier-wavelet combined domain filter method to remedy this shortage, which better preserves the original image information in the stripe-free locations.

Statistics-based methods are also commonly used for image destriping [11–16]. These methodological ideas assume that the distribution of the digital number for each detector approaches is the same, e.g., moment matching [11,14] and histogram matching [15]. The moment matching considers that the changes of the mean and standard deviation of each sensor are small, if this assumption holds, then these methods can remove stripe noise efficiently. The histogram matching is based on the assumption that the probability distribution of scene radiances seen by each sensor is the same. In general, statistics-based methods are easy to perform, and the computational process is fast, but these methods are greatly determined by the preestablish reference moment or histogram.

At present, optimization-based models have attracted many attentions and are widely applied to image destriping. Regarding the destriping problem as a conventional ill-posed inverse problem [17–21], existing regularization methods are employed to solve the destriping problem by introducing prior information. These methods compute the desired image by minimizing an energy function

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http://dx.doi.org/10.1016/j.neucom.2017.05.018

under some regularization terms. Shen and Zhang [17] established maximum a posteriori (MAP) framework and added Huber–Markov prior information for destriping and inpainting. In [18], the authors made the advantages of direction information of the stripes and proposed an unidirectional total variation (UTV) model to remove stripe noise. However, the method in [18] recognized the stripe regions and stripe-free regions inaccurately and produced a poor performance on heavy stripe noise. To overcome these weaknesses of UTV model, many researchers have proposed some modified UTV models [19,20,22,23]. In [20], the authors proposed a UTV-Stokes model, which avoids excessive over-smoothing by distinguishing stripe regions and stripe-free regions. In hyperspectral image destriping field, some researchers also considered the low-rank matrix recovery by exploiting the high spectral correlation between the latent image in different bands [24–26]. In [25], the authors proposed the graph regularizer low-rank representation (LRR) destriping method by incorporating the LRR technique, which is the first work to use LRR technique for destriping.

However, most of existing methods focus on directly estimating the clean image from observed one, paying much attention to the image itself, while without considering the directional and structural properties for the stripes, which would result in many image details may be removed along with stripes and residual stripes existing in the latent image. Recently, Liu et al. [27] obtains the destriping image from a novel perspective, which is first to estimate the stripe component and then utilizes the difference between observed image and stripe component to obtain the final destriping image. The global sparsity and local variational properties of the stripe component are considered in [27] to estimate the stripe component. The authors used ℓ_0-norm-based regularization to describe global sparse distribution of the stripes. But the ℓ_0-norm is non-convex, and global sparsity fails to reflect the inner structure of stripe component. Moreover, the sparsity property of stripes has disappeared when the stripes are too dense. To remedy this deficiency, the goal of this work is to focus on exploring stripes prior and achieving better stripe noise removal results.

In this paper, we introduce the group sparsity that is depicted by $\ell_{2,1}$-norm to describe the inner structure of stripe component and generate better results than recent state-of-the-art methods. Actually, the stripe image can be viewed as consisting of clean image and stripe component, and these two components can be regarded as equally. To obtain the clean image, which is equivalent to the problem of estimating the stripe component. Since the stripe component possesses line-by-line structures, we employ $\ell_{2,1}$-norm regularization to preserve the structure. Moreover, as the stripe noise has a clear directional feature, we also consider the differential properties of the along-stripe direction and across-stripe direction. Finally, we propose a novel optimization-based model for remote sensing image destriping problem. To solve the proposed convex model efficiently, an alternating direction method of multipliers (ADMM) based algorithm is developed to solve it. The main ideas and contributions of the proposed method are summarized as follows:

- As the stripe noise has obvious directional and structural properties, we employ these properties to construct a convex sparse optimization model that is solved by ADMM method. In particular, the convergence of the proposed method is guaranteed.
- We explore the group sparsity property of stripe noise in remote sensing image via implementing statistical analysis, and utilize $\ell_{2,1}$-norm regularization to depict the group sparsity property.
- Numerical experimental results, including simulated and real experiments, demonstrate that the proposed method outperforms the state-of-the-art results.

The rest of this paper is organized as follows. In the next section, we present the stripe component properties in details. In Section 3, the proposed model and optimization method are described. Section 4 presents some numerical experiments to demonstrate the effectiveness and satisfactory performance of the proposed method. Finally, we conclude paper in Section 5.

2. Stripe component properties analysis

Unlike other types of noises, the stripe noise has obviously directional and structural properties. How to design an appropriate regularization terms to describe these properties is the key issue in the stripe noise remove problem.

2.1. Problem formulation

The striping effects in remote sensing images are modeled as an additive noise [17,18], and thus the stripes degradation process can be formulated as

$$f(x,y) = u(x,y) + s(x,y), \tag{1}$$

where $f(x, y)$, $u(x, y)$, and $s(x, y)$ represent the degraded image from the detectors, the potential stripe-free image, and the stripe component at the location of (x, y), respectively. For the purpose of discussing numerical algorithm, a matrix-vector form of (1) can be rewritten as follows

$$\mathbf{f} = \mathbf{u} + \mathbf{s}, \tag{2}$$

where $\mathbf{f}$, $\mathbf{u}$, and $\mathbf{s}$ stand for the vectorized discrete version of $f(x, y)$, $u(x, y)$, and $s(x, y)$, respectively. In previous works, most of destriping methods aim to directly compute stripe-free image $\mathbf{u}$ from the degraded image $\mathbf{f}$. However, here we change our perspective to explore the further properties of stripe noise and propose a more efficient method to remove stripe noise and retain pixel values of stripe-free regions. This paper concentrate on extracting the stripe component $\mathbf{s}$ from degraded image $\mathbf{f}$. The framework of the proposed method is illustrated in Fig. 1.

2.2. Directional and structural properties of stripe component

To precisely estimate the stripe component, the key issue now is to excavate the properties of stripe component, and to depict them in appropriate regularization terms. Firstly, we use statistics-based method [16] (SLD) which achieves destriping by estimating the stripe component to remove stripe noise in MODIS image. In the meanwhile, we show the gradients of the stripe image at two directions: horizontal and vertical direction, and the results as shown in Fig. 2. From the results, we can find that the stripe component possesses directional property and structural property.

(1) *Directional property*: Figs. 2(d)–(e) show the gradients of stripe component in horizontal and vertical direction. From which, we can observe that the vertical gradient is quite sparse that indicates the stripe component has good smoothness in vertical direction. To preserve the stripe gradient well in vertical direction, we employ the sparse regularization on gradient domain to constrain it. The best choice is to employ ℓ_0-norm [27] that counts nonzero-element-number or hyper-Laplacian prior distribution that is depicted by ℓ_p-norm $(0 < p < 1)$ [28]. However, these are non-convex problems, and the globally optimal solution is hard to find. In addition, the results of ℓ_0 norm and ℓ_p norm are sensitive to the initial point, and the convergence of algorithm fail to guarantee. Here, we use ℓ_1-norm which is a convex function as the sparse regularization that is given as

$$R_1(\mathbf{s}) = \|\nabla_y \mathbf{s}\|_1, \tag{3}$$

where ∇_y denotes the linear first-order difference operators in vertical direction.