Infrared Physics & Technology 75 (2016) 1–11

Contents lists available at ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Unidirectional total variation destriping using difference curvature in MODIS emissive bands

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HIGHLIGHTS

- A novel destriping method of MODIS emissive bands is proposed.
- Spatial information extracted by the difference curvature is utilized to construct the spatially weighted parameters.
- Split Bregman iteration method is employed to optimize the proposed model.

ARTICLE INFO

Article history:
Received 2 July 2015
Available online 29 December 2015

Keywords:
MODIS
Unidirectional total variation
Difference curvature
Destriping
Split Bregman iteration

ABSTRACT

This paper presents a method of unidirectional total variation destriping using difference curvature in MODIS (Moderate Resolution Imaging Spectrometer) emissive bands. First, difference curvature is utilized to extract spatial information at each pixel; and the spatially weighted parameters that constructed by extracted spatial information are incorporated into the unidirectional total variation model to adaptively adjust the destriping strength for achieving a better destriping result and preserving the detail information meantime. Second, the split Bregman iteration method is employed to optimize the proposed model. Finally, experimental results from MODIS emissive bands and comparisons with other methods demonstrate the potential of the presented method for MODIS image destriping.

1. Introduction

The Moderate Resolution Imaging Spectrometer (MODIS), equipping a cross-track scanning radiometer with 36 spectral bands ranging from visible (0.4 μm) to long-wave infrared (14.4 μm), is remarkably designed to provide a wide range of remote sensing products for better understanding Earth climate and dynamic interactions among continent, ocean, and atmosphere [1]. The striping effect, a well-known artifact that compromises the radiometric integrity of collected data, commonly exists in MODIS emissive bands, severely degrades the quality of images, and inevitably limits the high-level applications for the normalized difference vegetation index, land surface temperature, and so on. Hence, it is indispensable and essential to remove the stripes before the succeeding image processing performing.

Quite a few studies have been done on how to remove stripe noise to improve the quality of images, and the approaches can be classified into several categories. The first category of destriping method is digital filtering in transform domain [2,3]. Being characteristic of periodicity, the frequency of stripe noise can be extracted using spectral analysis and filtered with an adequate low-pass filter or finite impulse response filter. However, some useful details with the same characteristics to the stripes would be inevitably filtered out, and some blurring would be brought in too.

The second category is the statistical destriping method, such as histogram matching [4,5] and moment matching [6]. It focuses on the statistical properties of data measured by each individual detector. This type of methods assumes that the distribution of each detector is identical, and the measurement of each detector is subsequently adjusted in order to match an imposed reference one. However, the performance of these methods is limited by the homogeneous area assumption.

The variational methods can be classified as the third category. These methods, proposed recently, consider the destriping problem as an inverse problem by optimizing an energy function. In this case, the destriping problem is to assume an image

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http://dx.doi.org/10.1016/j.infrared.2015.12.004
1350-4495/

observation model with which we can relate the desired image to the degraded one [7]. When striping effect is assumed to be an additive noise [8], the whole degradation model can be linearly described as

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

where $s(x, y)$ denotes the stripe noise, including detector-to-detector stripes, mirror-side stripes, and random stripes [9]. $u(x, y)$ and $g(x, y)$ are the latent image and observed degraded image, respectively.

Moreover, the purpose of this task is to estimate the desired image $u(x, y)$ from a given image $g(x, y)$ with stripe noise $s(x, y)$. Unfortunately, this system is underdetermined, and the solution is not unique. In order to yield a satisfactory result, an appropriate regularization term is introduced into the destriping model. Shen and Zhang [7] developed a maximum-a posteriori method based on a Huber–Markov regularization to solve destriping and inpainting problems for remote sensing images. Similarly to [7], Fehrenbach et al. [10] introduced a variational method to remove stationary noise in microscopy data. Viewing stripe noise as structural information, Bouali and Ladjal [11] presented a sophisticated unidirectional total variation model to remove stripe noise in MODIS data. Chang et al. [12] proposed a unified destriping framework combining unidirectional total variation and framelet regularization, in which the framelet regularization is adopted to preserve the detail information and suppress random noise. Chang et al. [13] went a step further and presented a joint variational framework with unidirectional total variation and spare representation to simultaneously destripe and denoise for remote sensing images.

In addition, some other destriping methods based on stripe detection are not classified into the above three categories. In those methods, stripes or defective lines are detected and restored by a moment-matching method or interpolation. Tsai and Chen [14] developed a destriping system involving two independent steps: detection and mending, in which the stripes are detected by edge-detection and line tracing, and restored by spline interpolation. Jung et al. [15] investigated and proposed an effective method to detect defective lines of the SPOT 4 SWIR image and to restore them by interpolation or moment-matching methods depending on the types of the defective lines.

Generally, there exist spatial property differences in the images of different regions, such as stripe regions and nonstripe regions, and the destriping strength should be adaptively adjusted in spatial property for different areas. How to deal with the spatial property differences is an important and challenging issue, for which difference curvature can be used to discriminate edges from flat and ramp areas in the images, and has been successfully adopted in previous studies for spatially adaptive weighted parameters construction [16,17]. In this paper, we present a method of unidirectional total variation destriping using difference curvature in MODIS emissive bands. First, difference curvature is used to extract spatial information at each pixel, and the spatially weighted parameters are constructed by the extracted spatial information. Among these parameters, the one from the region with stripes will be enforced a large weighted value to well remove stripe noise, while a small weighted value will be assigned in the nonstripe regions to preserve the detail information. In order to adaptively adjust the regularization strength, the spatially weighted parameters are incorporated into the unidirectional total variation model. For the optimization process, the split Bregman iteration algorithm, an efficient tool to solve ℓ_1 term, is employed. During the iteration, the spatially weighted parameters are updated iteratively to maintain a more accurate and robust constraint on spatial information.

The remainder of this paper is organized as follows. Section 2 describes the proposed model and the optimization method addressed for destriping process. Section 3 presents some results on synthetic and real images, and defines several indexes used to evaluate the destriping quality. Section 4 draws the conclusions.

2. Methodology

The destriping problem is formulated as an ill-posed inverse problem, and the total variation (TV) regularization, which has been widely used in computer vision for image denoising [18], image deblurring [19], and image super-resolution reconstruction [20], is introduced to yield a better destriping result. In literature [11], the unidirectional properties of stripe noise are fully exploited [Fig. 1]. The gradient along the stripes [Fig. 1(b)] is slightly influenced, while the gradient across the stripes [Fig. 1(c)] is seriously affected by stripes. It is a more realistic assumption that the gradient along the stripes is more suitable for a fidelity term of the destriping variation model, while the regularization term to process the noise component is isolated in the vertical gradient. In addition, an anisotropic total variation exhibits better performance than the isotropic one for destriping task [13]. Therefore, the destriping model has been effectively extended to the anisotropic unidirectional total variation. Furthermore, as there are many areas of different spatial property, the stripe noise reduction strength applied to every pixel should be adaptively adjusted accordingly to these areas.

Therefore, a model of unidirectional total variation destriping using difference curvature is constructed. Comparing to [11] and [12], a spatially weighted parameter $W(x, y)$ is employed and unified into the unidirectional total variation to adaptively adjust the regularization strength. The cost functional $E(u)$ is expressed as:

$$E(u) = \|\nabla_y(u-g)\|_1 + \sum_x \sum_y \lambda W(x,y) \|\nabla_x u(x,y)\|_1, \tag{2}$$

where λ is a regularization parameter that controls the trade-off along and across the stripes. ∇_x and ∇_y are the derivative operators in x and y axis, respectively; we define the direction along the stripes as y-axis, and the direction across the stripes as x-axis. $W(x, y)$ denotes the spatially weighted parameter at each pixel, which will be discussed in the next section. In formula (2), the first ℓ_1 term is the fidelity term that constrains the difference in the gradient between the desired image and striped image, while the second ℓ_1 term, named as regularization term, is applied to remove stripes.

In this paper, our primary objective is to set a spatial information constraint to adaptively adjust the regularization strength for achieving better destriping results while preserving the original detail information, and then a model of unidirectional total variation destriping using difference curvature is specifically introduced. The flowchart of the proposed model is drawn in Fig. 2, and the basic idea is stated as follows. Initially, difference curvature is utilized to extract spatial information at each pixel, and the spatially weighted parameter constructed by the extracted spatial information is unified into the unidirectional total variation model to adaptively adjust the regularization strength. And then, the split Bregman iteration method is adopted to optimize this model.

2.1. Spatially weighted parameter construction

Regions of different spatial property should have different regularization strength. In stripe regions, the larger regularization strength will be enforced to well remove the stripes, while the smaller regularization strength will be acquired to preserve the detail information in nonstripe regions. The difference in regularization strength of the proposed model can be explained by the spatial property differences. The more differences the spatial property have, the larger strength the regularization is, indicating