ISPRS Journal of Photogrammetry and Remote Sensing 66 (2011) 620–636

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

De-striping hyperspectral imagery using wavelet transform and adaptive frequency domain filtering

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A R T I C L E   I N F O

Article history:
Received 16 April 2010
Received in revised form 11 April 2011
Accepted 14 April 2011
Available online 17 May 2011

Keywords:
De-striping
Wavelet decomposition analysis
Fourier transform
Hyperspectral
De-noising

A B S T R A C T

Hyperspectral imagers are built line-by-line similar to images acquired by pushbroom sensors. They can experience striping artifacts due to variations in detector response to incident imagery. In this research, a method for hyperspectral image de-striping based on wavelet analysis and adaptive Fourier zero-frequency amplitude normalization has been developed. The algorithm was tested against three other de-striping algorithms. Hyperspectral image bands of different scenes with significant striping and random noise, as well as an image with simulated noise, were used in the testing. The results were assessed visually and quantitatively using frequency domain Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE) and/or Peak Signal-to-Ratio (PSNR). The results demonstrated the superiority of our proposed algorithm in de-striping hyperspectral images without introducing unwanted artifacts, yet preserving image details. In the noise-induced image results, the proposed method reduced RMSE error and improved PSNR by 3.5 dB which is better than other tested methods. A Combined method, integrating the proposed algorithm with a generic wavelet-based de-noising algorithm, showed significant random noise suppression in addition to stripe reduction with a PSNR value of 4.3 dB. These findings make the algorithm a candidate for practical implementation on remote sensing images including high resolution hyperspectral images contaminated with stripe and random noise.

1. Introduction

Remote sensing imagery is frequently contaminated with stripes, mainly due to differential variations in detector sensitivity to perceived energy. Whiskbroom scanners, such as Landsat Thematic Mapper (TM) and MODerate Resolution Imaging Spectroradiometer (MODIS) are subject to cross-track striping due to detector failure or differences in response to incident light (Chander et al., 2002; Wang et al., 2006). Such patterns are periodic and correspond to the number of detectors per scan (Schowengerdt, 2007). Pushbroom sensors are subject to in-track striping without scan periodicity as each line in the image is acquired simultaneously by hundreds or thousands of detectors in a cross-track array. Most hyperspectral imagery utilizes optical dispersion techniques to disperse the light entering through a narrow slit into a two-dimensional array, where one dimension represents the spatial component and the other dimension represents the spectral component (e.g. Anger et al., 1996; Cocks et al., 1998). In these systems, each captured image represents a line in the formed hyperspectral image. Adjacent lines are captured by moving the sensor to form a hyperspectral image cube. This configuration makes hyperspectral image acquisition similar to images acquired by traditional pushbroom scanners and subject to the same striping effect.

Image striping degrades image quality and risks its suitability for analysis. Image de-striping is one of the standard image preprocessing steps that is performed either through sensor calibration and/or image enhancement. Absolute radiometric calibration is conducted before launch for space-borne sensors. For airborne and ground-based sensors, absolute radiometric calibration is conducted periodically. However, cost and logistic issues may reduce the frequency of such calibration. Although, absolute radiometric calibration provides data that can be used to estimate sensor response, and hence leads to de-striped images, sensor detectors frequently deviate from their calibration values, which results in striped images. Over the years, many algorithms were developed to de-stripe remote sensing images captured by multiple sensors. Simple Linear Matching (SLM), histogram modification and matching algorithms were one of the earliest methods used for image de-striping (Horn and Woodham, 1979; Weinreb et al., 1989; Wegener, 1990). Gadallah et al. (2000) utilized a moment matching algorithm to de-stripe Landsat satellite imagery by matching each sensor response to a typical response. Such algorithms are built on the assumption that each detector views statistically similar

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0924-2716/$ - see front matter Published by Elsevier B.V. on behalf of International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS).
doi:10.1016/j.isprsjprs.2011.04.003

sub-scenes and requires large (extended) images (Gadallah et al., 2000). Additionally, some of the histogram matching algorithms tend to clip the high and low ends of the histograms, which results in a loss of image details (Singh, 1985).

Filtering has been widely used to reduce image striping. Filtering methods can be broadly divided into two categories: (i) filtering in image (spatial) domain, such as convolution filters and (ii) filtering in transformed domain, such as Fourier transform, wavelet decomposition, and Component Analysis (CA). Image domain low-pass directional filters (e.g. directional average filter) were used to reduce stripes but had the disadvantage of removing some image information (Chen et al., 2003). Oimoen (2000) proposed an improved filter that employed low-pass and high-pass filters alternately. In transformed domain, Minimum Noise Fraction (MNF) filtering was used effectively for non-directional noise reduction (Green et al., 1988). Filtering in Fourier transform domain, also termed as frequency domain filtering, is frequently used in removing periodic image striping artifacts. In this type of filtering, the image is transformed from the spatial to the frequency domain, where the filtering occurs. Srinivasan et al. (1988) proposed Fourier transformation to characterize and reduce striping effects of Landsat images. Liu and Morgan (2006) proposed selective and adaptive filtering algorithms in the Fourier domain to reduce complicated striping patterns. Fourier transform filtering achieved satisfactory results in the case of periodic stripe patterns, such as the ones resulting from single detector malfunctioning in Landsat images (Schowengerdt, 2007). Striping pattern is captured in the power spectrum as an elongated pattern in the direction perpendicular to the stripes. However, it is mixed with some image information, especially in the case of non-periodic stripes. Filtering such frequency domain patterns could lead to signal loss. Besides, many frequency domain filters are not fully automated requiring user input in developing filtering masks (Srinivasan et al., 1988; Liu and Morgan, 2006). These filters are still able to detect and filter periodic stripes adequately by targeting specific frequencies corresponding to the striping pattern without losing significant image details. However, non-periodic stripes, as in the case of pushbroom and hyperspectral images, possess a range of low to high frequencies. Filtering these frequencies leads to distorted image content and overall image blurriness.

Wavelet analysis receives an increasing attention as an efficient de-noising and de-striping technique for remote sensing images (Chen, 1997). Wavelet filtering is based on decomposing the image into components in different scale-space levels and filtering the decomposed components in these levels. Unlike Fourier transform analysis, where there is no direct link between the image representation in the spatial and frequency domains, wavelet decomposition maintains this relationship. Donoho and Johnstone (1994) proposed wavelet based de-noising techniques that reduces noise through hard- and soft-thresholding of wavelet detail components. Fukuda and Hirosawa (1999) utilized wavelet to filter speckle noise in Synthetic Aperture Radar (SAR) imagery. The authors highlighted how the filtering parameters (e.g. number of wavelet decomposition levels) affect filtering results including image smoothness. Wavelet was also used to filter high frequency variation in MODIS image time series (Lu et al., 2007; Chen et al., 2003).

Torres and Infante (2001) used wavelet transformation to analyze and reduce striping by eliminating directional wavelet detail components in the striping direction. This process is accompanied by a loss in other image information captured in the eliminated wavelet components. Other researchers (Chen et al., 2006; Munch et al., 2009) have refined the method by filtering rather than eliminating the wavelet components. Wang and Fu (2007) developed a method inspired by the striping power spectrum properties and based on Frequency domain filtering followed by a wavelet-based de-convolution. Despite being a promising approach, wavelet-based methods can produce unsatisfactory results as they have the potential to alter the content of the wavelet directional component and introduce image artifacts.

In this research, we propose an algorithm for de-striping hyperspectral images based on wavelet decomposition and adaptive Fourier zero-frequency normalization. In our method, the stripe-dominated directional wavelet components are filtered with an adaptive filter in the frequency domain to normalize against non-stripe features in the image wavelet components. We improved on existing wavelet-based de-striping methods (e.g. Torres and Infante, 2001; Munch et al., 2009) to overcome many of the artifacts introduced when de-striping high resolution edge-rich remote sensing images. We tested our method on images captured by a hyperspectral imaging sensor for a water body and vegetation scene, a Hyperion image and an image contaminated with simulated noise. We also tested a technique integrating our developed de-striping method with a standard wavelet based de-noising algorithm. We compared the results with three other de-striping methods including the traditional simple linear matching method and more recent wavelet-based methods using visual and quantitative assessments.

This paper is organized as follows. Section 2 provides the theoretical background for the Fourier and wavelet transforms used in this study. In Section 3, our developed de-striping methods are described and other methods used for comparison are briefly introduced. In this section, we also discuss the quality assessment metrics used in the research. In Section 4, the test images used in this study are introduced, and selection of optimal filtering parameters is discussed. Section 5 presents and compares the results of all tested methods using visual and quantitative assessments. Finally, Sections 6 and 7 discuss achieved results and provide the research conclusion, respectively.

2. Background

One of the motivations behind this research is to develop filtering algorithms that can efficiently minimize stripes and noise in high-resolution hyperspectral images. This type of noise occurs in the image acquisition direction (on-track direction) and is non-periodic in nature. Wavelet transform, as a multi-resolution and scale-space representation of the image, has the ability to separate directional noise in certain directional wavelet components at different scale levels. On the other hand, Fourier transform can analyze image noise in the frequency domain. As these transforms were incorporated in our proposed method, basic concepts of these transforms and their application in image filtering are reviewed in this section.

2.1. Fourier transform

Fourier transform decomposes the signal into an infinite set of sinusoidal waves of different frequencies, amplitudes and phases. It transforms the image from spatial domain to frequency domain entirely. The first component corresponds to the zero-frequency value that is the mean amplitude of the signal, also known as the Direct Current (DC) (Schowengerdt, 2007). For analyzing a discrete signal, Discrete Fourier Transform (DFT), which represents a finite sum of sinusoidal functions, is used. One-dimensional DFT is mathematically expressed as:

$$F_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi}{N} ikn} \quad k = 0, \ldots, N-1 \tag{1}$$

where the complex exponential term represents the sum of sine and cosine terms and i is imaginary number. F_k is known as Fourier coefficient.