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Removal of stripe noise with spatially adaptive unidirectional total variation

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ABSTRACT

Multi-detectors imaging system often suffers from the problem of the stripe noise, which greatly degrades the quality of the resulting images. To better remove stripe noise and preserve the edge and texture information, a robust destriping algorithm with spatially adaptive unidirectional total variation (SAUTV) model is introduced. The spatial information of the striping noise is detected by using the stripe indicator called difference eigenvalue, and a weighted parameter determined by the difference eigenvalue information is added to constrain the regularization strength of the UTV regularization. The proposed algorithm can effectively remove the stripe noise and preserve the edge and detailed information. Moreover, it becomes more robust with the change of the regularization parameter. Split Bregman method is utilized to efficiently solve the resulting minimization problem. Comparative results on simulated and real striped images taken with two kinds of imaging systems are reported.

1. Introduction

The stripe noises commonly exist in imaging systems with multi-detectors, such as Moderate Resolution Imaging Spectroradiometer (MODIS) images [1,2] and hyperspectral images [3]. These stripe noises severely limit the application of these images in the next phase. Therefore, it is critical to remove the stripe noise and improve the quality before the subsequent image interpretation processes. It is often assumed that the stripe noise is an additive noise [1], and the degradation process can be described as

$$g(x, y) = u(x, y) + n(x, y), \quad (1)$$

where $g(x, y)$ is the degraded image by the instrument at pixel (x, y), $u(x, y)$ is the latent image, and $n(x, y)$ is the stripe noise. How to estimate the latent image u from the observation g is an ill-posed inverse problem and regularization is necessarily introduced. In recent years, the total variation (TV) is widely used in many applications, mainly due to its desirable properties such as convexity and the ability to preserve sharp edges [1,2,4]. In the MAP framework, Shen [2] firstly proposed a maximum-a-posteriori based method with a Huber-Markov prior to destripe, which means the prior term is an alternative between the TV regularization and Tikhonov regularization.

In [1], the authors proposed a more sophisticated unidirectional TV (UTV) model to remove this type of noise, which assumes the gradients along the stripe lines are not affected by the stripe noise. Their method presents impressive destriping results. However, there are certain weaknesses in their proposed model. First, the authors applied the standard gradient-descent algorithm to solve their model. Thus, the time step should be well selected, or else, it may require significant processing time to gain a satisfactory solution. Second, the stripe noise and the useful information of the image such as edge and other details are treated in the same way which means the important image features will be more easier filtered out as the stripe noise is removed. These drawbacks of the algorithm in [1] limit its practical application. In [5], the authors also made use of the directional character via the wavelet decomposition, and then employed the Fourier filters to remove the stripes in the specific bands. To obtain the appealing destriping result, we have to manually adjust some parameters.

To overcome the shortcomings in [1], an improved UTV algorithm with spatially adaptive unidirectional total variation (SAUTV) is introduced. In this work, the spatial information of the striping noise was detected by using the stripe indicator called difference eigenvalue, which enable us to automatically balance the regularization strength between different spatial property regions in an image. The regions containing the striping noise will be enforced with a large regularization strength while a small regularization strength is imposed on nonstripe regions for preserving the edges and details. What is more, the proposed algorithm becomes more robust with the change of the regularization parameter. In addition, considering the computational complex of SAUTV model, a

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faster technique such as split Bregman method is applied to solve the SAUTV based destriping algorithm which requires less processing time. Its basic idea is to introduce an auxiliary variable to decompose a complex optimization problem into two independent subproblems, which are easy to implement.

The letter is organized as follows. Section 2 describes the proposed algorithm in detail. Experimental results are describes in Section 3. Finally, the conclusions are drawn in Section 4.

2. Proposed algorithm

In [1], the authors exploited an unidirectional properties of scan line noise and incorporated the properties based on UTV into a variational framework. In this framework, destriping can be viewed as an optimization problem based on the minimization of the following unidirectional variational model:

$$\min_u \|\nabla_x(u-g)\|_1 + \lambda\|\nabla_y u\|_1, \tag{2}$$

where the first term $\|\nabla_x(u-g)\|_1$ and second term $\|\nabla_y u\|_1$ denotes the horizontal (cross-track) and vertical (along-track) variations of the image u respectively. λ is the regularization parameter which plays a very important role. It controls the UTV regularization strength. If λ is too small, the stripe noise will not be well removed; inversely, if it is too large the detailed information such as edge will be blurred. It means that the regularization parameter λ is spatially dependent. Therefore, in this research, a spatially weighted UTV regularization considering the spatial property of the image is introduced. A key issue is to select a good spatial striping indicator, which can distinguish striping noise from other nonstripe regions. To do this, the stripe indicator called difference eigenvalue [4] was used to detect the spatial information of the striping noise including its position and intensity. The difference eigenvalue is based on the Hessian matrix of the image

$$H = \begin{bmatrix} u_{xx} & u_{xy} \\ u_{yx} & u_{yy} \end{bmatrix}, \tag{3}$$

where u_{xx}, u_{xy}, u_{yx}, and u_{yy} are the second derivatives of u. The two eigenvalues of the H, denoted by λ_1 and λ_2 are given by:

$$\lambda_{1,2} = \frac{1}{2}[(u_{xx}+u_{yy}) \pm \sqrt{(u_{xx}-u_{yy})^2 + 4u_{xy}^2}]. \tag{4}$$

Let λ_1 denote the larger eigenvalue and λ_2 denote the other one. The difference eigenvalue edge indicator $d(x, y)$ is defined as

$$d(x,y) = (\lambda_1-\lambda_2)\lambda_1\delta(x,y), \tag{5}$$

where $\delta(x, y)$ is a local variance image of u

$$\delta(x,y) = \frac{1}{9}\sum_{i=-1}^{1}\sum_{i=-1}^{1}[u(x+i,y+j)-u(x,y)]. \tag{6}$$

Thus, the stripe indicator is defined as following:

$$D(x,y) = G_\sigma \otimes \sqrt{(\nabla_x d)^2 + (\nabla_y d)^2}, \tag{7}$$

where G_σ denotes the Gaussian kernel with the parameter σ (the size is 3×1, $\sigma = 1$ in this paper), $\otimes$ is the convolution operator. Combining the stripe indicator into UTV model, we define a novel SAUTV model with spatially adaptive property:

$$\text{SAUTV} = \sum_x\sum_y W(x,y)|\nabla_y u(x,y)|, \tag{8}$$

where $W(x, y) = \mu D(x, y)/(1 + \mu D(x, y))$ is the spatially adaptive weight. Substituting the UTV term in (2) with SAUTV in (8), we introduce the cost functional:

$$E(u) = \|\nabla_x(u-g)\|_1 + \sum_x\sum_y \lambda W(x,y)|\nabla_y u(x,y)|. \tag{9}$$

Thus, our method is to seek the optimal u that minimize $E(u)$. The difficulty for solving (9) is that the ℓ_1 term is nondifferentiability and inseparable. To overcome this problem, we use split Bregman method. The split Bregman method is first introduced in [7] as a very efficient tool to solve the general ℓ_1-regularized optimization problems. The basic idea is to convert the unconstrained minimization problem in (9) into a constrained one by introducing two auxiliary variables $d_x = \nabla_x(u-g)$ and $d_y = \nabla_y u$. This leads to the constrained problem:

$$\min_{u,d_x,d_y} \|d_x\|_1 + \sum_x\sum_y \lambda W(x,y)|d_y(x,y)|, \quad \text{s.t. } d_x = \nabla_x(u-g) \text{ and } d_y = \nabla_y u. \tag{10}$$

Then, with strictly enforcing the constraints by applying the Bregman iteration, the problem (10) could be further transformed into a nonconstrained minimization problem:

$$\min_{u,d_x,d_y} \|d_x\|_1 + \sum_x\sum_y \lambda W(x,y)\|d_y\|_1 + \frac{\beta}{2}\|d_y - \nabla_y u - b_y\|_2^2 + \frac{\alpha}{2}\|d_x - \nabla_x(u-g) - b_x\|_2^2, \tag{11}$$

where α and β are two positive penalization parameters. We now investigate these subproblems one by one.

(1) The u-related subproblem is

$$\min_u \frac{\alpha}{2}\|d_x - \nabla_x(u-g) - b_x\|_2^2 + \frac{\beta}{2}\|d_y - \nabla_y - b_y\|_2^2, \tag{12}$$

which is a least-square problem. It is equivalent to the following linear system:

$$\alpha\nabla_x^T\nabla_x(u^{k+1}-g) + \beta\nabla_y^T\nabla_y u^{k+1} = \alpha\nabla_x^T(d_x^k - b_x^k) + \beta(d_y^k - b_y^k), \tag{13}$$

because the system is strictly diagonal, the Gauss–Seidel solution to this problem can be written componentwise as $u_{i,j}^{k+1} = G_{i,j}^k$, where

$$\begin{aligned} G_{i,j}^k = {} & \frac{\alpha}{2\alpha+2\beta}(u_{i+1,j}^k + u_{i-1,j}^k + 2g_{i,j} - g_{i+1,j} - g_{i-1,j}) \\ & + \frac{\alpha}{2\alpha+2\beta}(b_{x,i+1,j}^k - b_{x,i,j}^k + d_{x,i,j}^k - d_{x,i+1,j}^k) \\ & + \frac{\beta}{2\alpha+2\beta}(u_{i,j+1}^k + u_{i,j-1}^k + b_{y,i,j+1}^k - b_{y,i,j}^k + d_{y,i,j}^k - d_{y,i,j+1}^k). \end{aligned} \tag{14}$$

(2) d_x-related subproblem is

$$\min_{d_x} \|d_x\|_1 + \frac{\alpha}{2}\|d_x - \nabla_x(u-g) - b_x\|_2^2, \tag{15}$$

it can be computed using the standard soft-threshold formula in [8]

$$d_x^{k+1} = \text{shrink}(\nabla_x(u^{k+1}-g) + b_x^k, 1/\alpha), \tag{16}$$

where

$$\text{shrink}(x,r) = \frac{x}{|x|}\max(|x|-r, 0). \tag{17}$$