remote sensing image striping noise algorithm based on region-weighted double sparse constraint

Yi Zheng¹, Feng Zhou² and Guoyou Wang¹*

¹ School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan, Hubei, 430000, China
² School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan, Hubei, 430000, China
*Corresponding author’s e-mail: M201872647@hust.edu.cn

Abstract. Infrared remote sensing image has been used in many fields such as land cover crop monitoring, climate monitoring, military strike and early warning. In spaceborne remote sensing imaging system, the stripe is a common noise, seriously affects the researchers’ study of the ground scene. In recent years, the framework that researchers based on different principles use a variety of methods to remove fringe noise in infrared remote sensing images is proposed, such as filtering based method, the method based on statistics, however, most current algorithm still exist the following two problems: some structure or texture was easy to be mistaken as the stripe noise and removed, lost the original information of the image; in some bright or dark areas, it is easy to create artificial traces, adding redundant information and making the denoising result look unnatural. In view of the above two problems, this paper will analyse the causes of the problems and propose a stripe noise removal algorithm based on the region-weighted double-sparse constrained unidirectional variational model, which can effectively reduce the above two phenomena.

1. Introduction
In this paper, the shortcomings of the unidirectional variable-grade local optimization model for removing the stripe noise in infrared images are analysed, and the strategy of de-noising in different regions is proposed. Different noise estimation methods are adopted in different regions to improve the regional adaptability of the model. In order to reduce the striping noise, while removing the real noise, the method will also smooth out some similar structures and details with the striping, a double sparse constraint, namely global sparse and unidirectional gradient sparse, is proposed to normalize the estimated striping noise, making the estimated striping noise more orderly. A unidirectional variational optimization model with regional weighted double sparse constraints was established to estimate the stripe noise, and the ADMM optimization algorithm was used to solve the model iteratively. The typical infrared remote sensing images of various scenes were collected to carry out simulation strip and real strip experiments. Experimental results show that the proposed region-weighted double-sparse constrained unidirectional variational optimization model has better stripe removal performance than the current mainstream stripe removal algorithm, including the estimation of stripe noise, the preservation of the detailed structure (similar to that of stripe), and the generation of fewer artificial traces.
2. Analysis of strip noise characteristics

In the scanning imaging system, stripe noise is easy to appear in the captured infrared image due to the inconsistency of correction of each detector element. According to the imaging principle, the stripe noise generally only appears in one direction of the image, but does not exist in the other direction. Two typical infrared remote sensing images with stripe noise are shown in Figure 1.

(a) Terra MODIS Data band 27  
(b) Terra MODIS Data band 34

Figure 1  Typical infrared remote sensing stripe noise image

In general, a noisy image can be expressed as the sum of a clean image and a noisy image:

\[ Y(u, v) = X(u, v) + S(u, v) \]  \hspace{1cm} (1)

\( X \) is an ideal clean image, \( S \) represents stripe noise.

Due to the good directionality of stripe noise, the gradient of most noise-polluted pixels along the stripe direction is much smaller than that along the vertical stripe direction. This property can be expressed as:

\[ \frac{\partial Y}{\partial u} \ll \frac{\partial Y}{\partial v} \]  \hspace{1cm} (2)

Through analysis and research, we find that the sparse feature also exists in the gradient domain of the image, that is, the gradient in the direction of the edge band. Therefore, the gradient prior constraints of the constructed strips are as follows:

\[ R_z(S) = \| \nabla_u S \|_o \]  \hspace{1cm} (3)

3. A region-weighted double-sparse constrained unidirectional variational strip-removing model

The use of sections to divide the text of the paper is optional and left as a decision for the author. Where the author wishes to divide the paper into sections the formatting shown in table 2 should be used.

3.1. Infrared remote sensing image region segmentation

An infrared remote sensing image is divided into three regions: normal region, extreme region and extreme stripe region. In the extreme region, the gray-scale value of the image pixel is almost 0 or \(2^N-1\), and \(N\) is the number of pixels. The extreme value of the extreme region is caused by the natural radiation of the scene. Here we collectively call the extremely bright region and the extremely dark region as the extreme value region (EA) or the strong stripe region (SSA). The gray-scale value in the extremely dark region and the extremely dark strip is almost zero, so a very small field value can be selected to detect them. Once the two areas have been detected, the next step is to separate them. A significant difference between the extremely dark stripe region and the extremely dark stripe region is that the width of the extremely dark stripe is finite in the direction of the vertical stripe, which is smaller than the width of the stripe, while the width of the extreme stripe region is unlimited and can be of any size. For example, in MODIS images, the width of the bands is 2. According to this feature, extremely
dark region and extremely dark strip can be distinguished. In the direction of vertical stripe, when the number of neighbourhood extrema of a pixel exceeds a certain value, it is judged as extremely dark region; otherwise, it is judged as extremely dark strip.

3.2. Weighted double sparse constrained optimization model

Different noise estimation techniques should be adopted in different regions of striped noise images. In the extremum area, there is no noise (or the stripe noise is submerged by extremum radiation), and the pixel value can maintain the original gray-scale value. In the extremum stripe region, the texture has been completely destroyed, and the surrounding region information needs to be used to estimate the damaged texture. Repair of a texture in a given area can be done using an inpainting-like approach, but they usually require a large clean image around the patched area as a reference, or use multi-band information to supplement it, and are computationally heavy. We choose to use a unidirectional diffusion method to estimate the texture content destroyed by strong stripe noise. Let the extremum region be, and the strong band region be, then the indicator functions of the two special regions can be respectively expressed as:

\[
W_s(u,v) = \begin{cases} 
0, & \text{if } (u,v) \in \Psi_s \\
1, & \text{otherwise}
\end{cases}
\]  

(4)

(4)

\[
W_e(u,v) = \begin{cases} 
0, & \text{if } (u,v) \in \Psi_e \\
1, & \text{otherwise}
\end{cases}
\]  

(5)

Combined with the DSUV model, strong stripe indicator factor \( W_s \) and extreme region indicator factor \( W_e \), a DSUV model with stronger robustness is proposed in this paper. The region-weighted double-sparcity constrained single-direction variational model (denoted as WDSUV) is proposed, and the objective function is expressed as:

\[
J(S) = \|W_s \nabla_y S\|_{p} + \lambda_1 \|W_e \nabla_y (Y - S)\|_{q} + \lambda_2 \|S\|_0 + \lambda_3 \|\nabla_y S\|_1.
\]  

(6)

It is easy to see that the WDSUV model is a generalization of UV and SUV.

3.3. Solve the optimization model with regional weighted double sparse constraints

The previous section introduces the WDSUV model. In this section, ADMM (Alternating Direction Method of Multipliers) optimization method is used to solve the model. ADMM is based on introducing auxiliary variables and iteratively updating each variable to solve the original optimization model, which has good stability and fast convergence ability. After the introduction of ADMM optimization technology, the original optimization model can be decomposed into four submodels, which can be solved quickly by using soft domain value operator, hard domain value operator and mixed domain value operator. After several iterations, the algorithm converges to a stable solution and estimates the stripe noise \( S \).

4. Experiments

This section will be based on regional weighted double sparse constraint single direction variational model experiment, and compared with algorithm based on the several typical to stripe noise, including the method based on spatial domain filtering GF-based to stripe noise method, the method based on frequency domain filtering WAFT, UV model based method, Including UV model, HUTV, SUV, and based on the deep learning to SNRCNN stripe noise method. It is also compared with the classical denoising algorithm M=BM3D.

4.1. Comparison of quantitative indicators

This section will carry out quantitative index analysis on the performance of each algorithm in real stripe noise images. Since there is no real clean image for reference, PSNR and SSIM indexes cannot be
calculated, we use the following three non-reference indexes, namely MICV, MMRD and line mean curve. The MICV indicator measures the degree of change in the subregions of the image:

The MICV index is usually calculated by selecting relatively smooth subregions of the image. In general, the larger the MICV value, the smaller the MMRD, indicating better striping performance.

Table 1 lists the comparison of MICV and MMRD indexes of each algorithm in real strip-noise images. As for the MMRD index, except R3, the model WDSUV mentioned in this chapter has reached the minimum value. For the MICV metric, in R1, R4, and R5, the MICV value of WDSUV is smaller than that of HUTV, mainly because HUTV over-smooths some of the details in the image.

4.2. Subjective visual contrast
This section will carry out quantitative index analysis on the performance of each algorithm in real stripe noise.

From the generated image in Figure 2, it can be seen that WAFT, UV, HUTV, SUV can not effectively maintain the gray-scale level of the extreme area, they will produce fuzzy and other artificial traces in the extreme area. In the aspect of restoring the texture of SSA region, most algorithms (including SUV) will produce stripe trace, while the proposed WDSUV model can adaptively segment the extreme region and strong stripe region, design reasonable weight, maintain the gray invariance of the extreme region, and re-estimate the texture damaged by strong stripe noise.
5. Conclusion
Experiments show that the proposed WDSUV stripe removal algorithm can make the estimated stripe noise more regular and smooth, and can effectively maintain some small-scale structural details. However, when there are some small-scale stripe noises in the image, the proposed model may also save them in the de-noising results, and the output results contain some tiny stripe residues. It is worth further investigating how to distinguish small stripe noise from real texture details.

Acknowledgments
This work is supported by Image Processing & Intelligent Key Laboratory in Huazhong University of Science and Technology. Thank my tutor Guoyou Wang for his guidance.

References
[1] Goodall T R, Bovik A C and Paulter N G. Tasking on natural statistics of infrared images [J]. IEEE Transactions on Image Processing, 2016, 25 (1): 65-79.
[2] Two-point correction and minimum filter-based nonuniformity correction for scan-based aerial infrared cameras [J]. Optical Engineering, 2012, 51: 13.
[3] Sheng M, Xie J and Fu Z. Calibration-based NUC Method in Real-time Based on IRFPA [J]. Physics Procedia, 2011, 22: 372-380.
[4] Shi Y, Zhang T and Cao Z. A New Piecewise Approach for Nonuniformity Correction in IRFPA [J]. International Journal of Infrared and Millimeter Waves, 2004, 25 (6): 959-972.

[5] Liang K, Yang C, Peng L and Zhou B. Nonuniformity correction based on focal plane array temperature in uncooled long-wave infrared cameras without a shutter [J]. Applied Optics, 2017, 56 (4): 884-889.

[6] Huo L, Zhou D, Wang D, Liu R and He B. Staircase-scene-based nonuniformity correction in aerial point target detection systems [J]. Applied Optics, 2016, 55 (25): 7149-7156.

[7] Harris J G and Yu-Ming C. Nonuniformity correction of infrared image sequences using the constant-statistics constraint [J]. IEEE Transactions on Image Processing, 1999, 8 (8): 1148-1151.

[8] Zhang C and Zhao W. Scene-based nonuniformity correction using local constant statistics [J]. Journal of The Optical Society of America A-optics Image Science and Vision, 2008, 25 (6): 1444-1453.

[9] Zuo C, Chen Q, Gu G, Sui X and Qian W. Scene-based nonuniformity correction method using multiscale constant statistics [J]. Optical Engineering, 2011, 50 (8): 12.

[10] Geng L, Chen Q and Qian W. An Adjacent Differential Statistics Method for IRFPA Nonuniformity Correction [J]. IEEE Photonics Journal, 2013, 5 (6): 6801615.

[11] Zhou D, Wang D, Huo L, Liu R and Jia P. Scene-based nonuniformity correction for airborne point target detection systems [J]. Optics Express, 2017, 25 (13): 14210-14226.

[12] Zuo C, Chen Q, Gu G and Qian W. New temporal high-pass filter nonuniformity correction based on bilateral filter [J]. Optical Review, 2011, 18 (2): 197-202.

[13] Cheng K, Zhou H, Rong S, Qin H, Lai R, Zhao D and Zeng Q. Temporal high-pass filter nonuniformity correction algorithm based on guided filter for IRFPA [C]. In: Proceedings of the Applied Optics and Photonics China (AOPC2015), Beijing, China, 2015, 6.

[14] Li Z, Shen T and Lou S. Scene-based nonuniformity correction based on bilateral filter with reduced ghosting [J]. Infrared Physics & Technology, 2016, 77: 360-365.

[15] Zhou H-X, Qin H-L, Lai R, Wang J and Bai L-P. Nonuniformity correction algorithm based on adaptive filter for infrared focal plane arrays [J]. Infrared Physics & Technology, 2010, 53: 295-299.