MULTISPECTRAL DENOISING FOR MULTI-PURPOSE SATELLITES IMAGING SENSOR USING WAVELET DOMAIN DEEP RESIDUAL LAERNING

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ABSTRACT: Multi-purpose satellites have the advantage of acquiring multi-band images such as RGB and near-infrared (NIR) bands via image sensors. Multispectral images can be used in many applications and the variety of bands increases the utilization of satellites. However, various noises in images degrade the quality of scenes, which limits the use of satellite imagery. There are two types of noises in images of high-resolution satellites: vertical stripe noise and horizontal wave noise. Conventional model-based denoising methods have been developed using predefined features or prior knowledge of scenes. In model-based approaches, however, performance degradation occurs when the pre-assumed model fails. To tackle this problem, we propose a multispectral image denoising method using convolutional neural network (CNN) in the wavelet domain for the removal of vertical stripe noise and horizontal wave noise. Given that the noise artifacts have directional components, the proposed deep neural network is designed in the wavelet domain to extract and process directional features of noises, and trained in a supervised manner using the wavelet coefficients of the model-based reconstruction results. Our experimental results show that the proposed method effectively removes vertical stripe noise and horizontal wave noise in images. Moreover, by synergistically learning the image statistics from the model-based label data, the proposed neural network produces improved denoising performance without sacrificing the image resolution. Furthermore, we have demonstrated that CNN in the wavelet domain preserves more detail than CNN in the image domain when denoising multispectral satellite imagery.

1. INTROUDCTION

Multi-purpose satellites are applicable in a variety of fields because of their different image sensors. For instance, multispectral image sensors captures images for red (R), green (G), blue (B), and near-infrared (N) bands. Each band image has different characteristics, which leads to the use of satellite imagery for many applications such as urban planning, traffic monitoring, agriculture development, and location-based services.

However, satellite images are contaminated with various noise during the image acquisition phases, which limits the use of satellite imagery. In particular, there are various sources of noise such as hardware characteristics, sensitivity of image sensors, system calibration errors, and thermal noise. In order to effectively use satellites imagery, the development of a denoising algorithm is necessary. In this study, we focused on removal of two types of noise in satellite images: vertical stripe noise and horizontal wave noise. Examples of vertical stripe noise and horizontal wave noise are shown in Figure 1. These two types of noise patterns affect the quality of images and limit the use of satellite imagery.

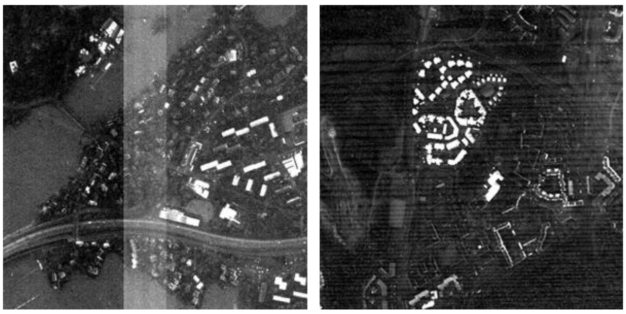


Figure 1. Examples of vertical stripe noise pattern (left) and horizontal wave noise pattern (right).

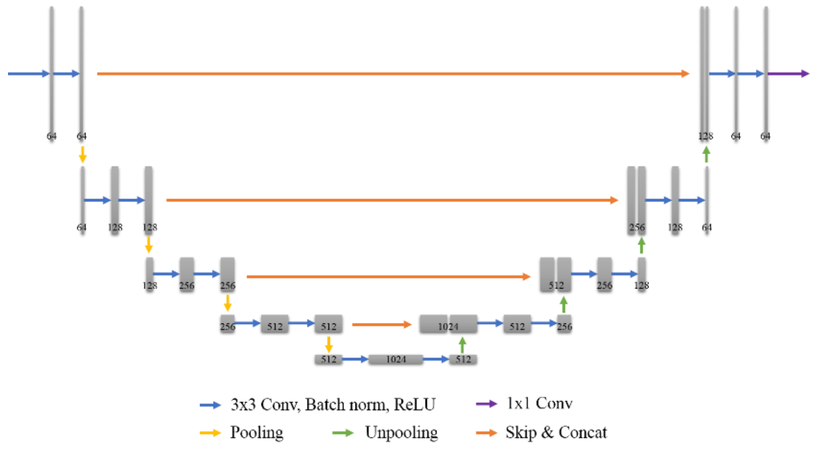


Figure 2. The architecture of the proposed denoising network.

Various denoising methods have been developed for satellite imagery. Most traditional denoising methods for satellite imagery use model-based approaches. Typically, model-based denoising methods are based on hand-crafted features or prior knowledge of images. For instance, multispectral images were considered as spectral-spatial images and anisotropic spectral-spatial total variation were used to remove stripe patterns in satellite images (Chang, 2015). Tensor-based approach with intrinsic tensor sparsity regularization were used to remove various noise in multispectral images (Xie, 2016). The related bands, selected based on prior knowledge of data, were fused to utilize spatial correlation between different bands (Zheng, 2018). The limitation of the model-based approaches is performance degradation when pre-defined features and prior knowledge of data do not fully reflect the nature of new data. Recently, convolutional neural networks (CNN) have shown recent advances in image denoising tasks (Zhang, 2017 and Ulyanov, 2018). The advantage of CNN is that CNN can automatically learn high-level features optimized for the task based on training data. In the field of remote sensing, denoising methods using CNN have also been proposed (Chang, 2018 and Liu, 2019). However, image domain learning approaches have been used in most CNN-based methods for denoising satellite images, which possibly blur edges and details of images.

In this study, we propose a multispectral denoising method using wavelet domain deep residual learning for satellites imagery. Our method uses CNN for the removal of vertical stripe noise and horizontal wave noise. Since our target noises have directional properties, the proposed deep neural network is designed in the wavelet domain to effectively extract directional components of noises. Our network is trained in a supervised manner using the wavelet coefficients of the conventional model-based results. Our results show that the proposed method effectively removes vertical stripe noise and horizontal wave noise without removing edges and details in satellite images. Moreover, by learning the image statistics from the conventional model-based results, the proposed method shows improved denoising performance. Furthermore, we have demonstrated that CNN in the wavelet domain preserves more detail than CNN in the image domain when denoising multispectral satellite imagery.

2. METHODS

2.1 Data preparation

Multispectral images from the high-resolution satellite are utilized in the study. We used multiband images consisting of red, green, blue and near-infrared bands. For the task of removing vertical stripe noise, 26 blue band images were used. The conventional model-based denoising results were used as labels for training our convolutional neural network. For the task of denoising horizontal wave noise, we utilized 16 spatially matched RGBN images. The corresponding model-based denoising results contain only green band images. To train and evaluate our network, we set the upper half of images as training set and otherwise as test set.

2.2 Network Structures

To extract and utilize directional components of noise patterns, two level discrete Haar wavelet transform was used. The wavelet coefficients of the input image are inputs of denoising network, and the wavelet coefficients of the target image are considered as labels. By using discrete Haar wavelet transform, several subbands can be acquired: LL

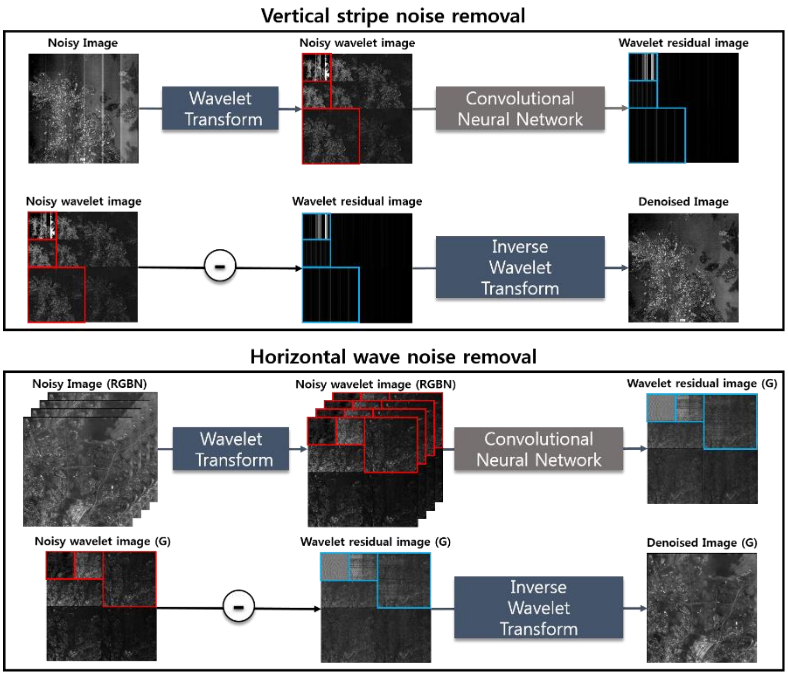


Figure 3. The proposed denoising scheme for vertical stripe noise (top) and horizontal wave noise (bottom).

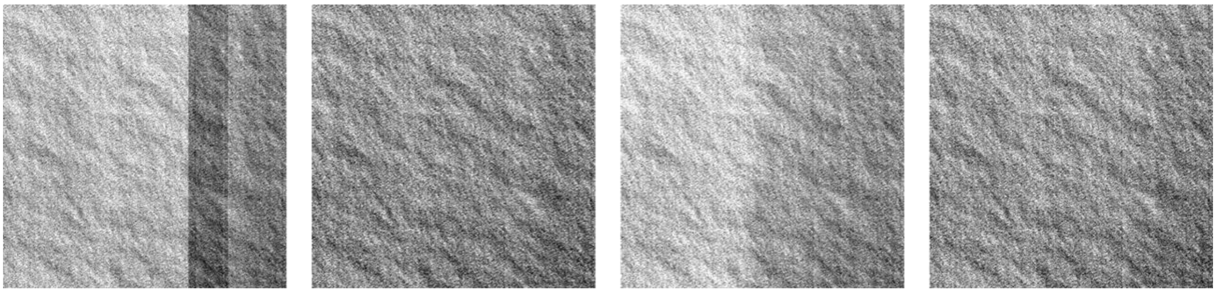
(approximation), HL (vertical detail), LH (horizontal detail), and HH (diagonal detail) bands. To preserve edges and details in images, we reconstructed selected bands based on the properties of noise patterns. For the vertical stripe noise with vertical structures, LL2, HL2, and HL1 bands were reconstructed by the denoising network. In the case of horizontal wave noise, we reconstructed LL2, LH2, and LH1 wavelet coefficients using the denoising network. The advantage of reconstructing only selected bands is that the noise can be removed without discarding edges and details in other bands. We followed residual learning scheme in which label images were calculated from the difference of input images and conventional model-based results in the wavelet domain. For each reconstruction problem, we trained independent denoising networks for each selected band: three independent networks for vertical stripe noise and three independent networks for horizontal stripe noise.

The denoising network is constructed based on U-net structures (Ronneberger, 2015), as shown in Figure 2. We used 3×3 convolution with batch normalization and rectified linear unit (ReLU) as a default operation for convolutional layers. Skip connections and concatenations are added to exploit low-level features. Pooling layer consists of 2×2 max pooling, while bilinear interpolation is used for unpooling operation. We set the l_2 loss as a reconstruction loss. The inputs are wavelet coefficients of the input image. The targets are wavelet coefficients of difference image of the input and the conventional model-based result. We randomly cropped patches from wavelet coefficients of images. The size of patches is 128×128. To train the network, we used Adam optimizer. The initial learning rate was 10^{-4} and decreased to 0 until 10^5 epochs. The mini-batch size was 16. Pytorch library was used for the experiments.

Figure 3 shows overall denoising scheme for vertical stripe noise and horizontal wave noise. After training the network, the denoised image can be reconstructed using the proposed scheme. At the first stage, two level discrete Haar wavelet transform is conducted to the input image to get decomposed subband images. Second, our denoising network produces the wavelet residual image from the noisy wavelet image. The clean wavelet image can be calculated by the difference of noisy wavelet image and wavelet residual image. Finally, the denoised image is reconstructed by inverse discrete wavelet transform. To remove noise components with preserving edges and details, we reconstructed only selected bands based on the property of noise, while using non-selected bands without modification. As shown in Figure 3, we used only a single blue channel for vertical stripe noise removal. When eliminating horizontal wave noise, spatially matched RGBN images are utilized. Our hypothesis is that by using spatially matched RGBN images, the network can use spatial correlation between channels, resulting in an improvement of performance.

3. RESULTS AND DISCUSSIONS

To evaluate the performance of our method for the vertical stripe noise, we compared our results with conventional



(a) (b) (c) (d)

Figure 4. Results of vertical stripe noise removal for the first sample. (a) Noisy input image, (b) Our result, (c) Result of image domain deep learning, (e) Result of conventional model-based reconstruction.

(a) (b) (c) (d)

Figure 5. Results of vertical stripe noise removal for the second sample. (a) Noisy input image, (b) Our result, (c) Result of image domain deep learning, (e) Result of conventional model-based reconstruction.

model-based results by visual inspection. Furthermore, we made results of image domain deep learning to investigate the advantages of wavelet domain deep learning. We used same architecture and training scheme as our method without wavelet transform. Figure 4 and Figure 5 show results of vertical stripe noise removal for the first sample and the second sample. 200×200 patches were cropped from the scenes for the visualization. As shown in Figure 4 and Figure 5, our method effectively removes vertical stripe noise patterns without sacrificing edges and details of input images. Results of image domain show remaining stripes and inhomogeneity, which means wavelet domain learning is a better learning strategy for removing vertical stripe noise. By decomposing the image into subbands by wavelet transform and using selected bands based on the noise characteristic, the network can easily learn the statistics of the directional components of the noise and make improved results.

We compared our results for the removal of horizontal wave noise with conventional model-based results by visual inspection of reconstruction results and difference images. To examine the benefits of wavelet domain deep learning and the use of multiband images, we produced the outcomes of wavelet domain deep learning and image domain deep learning with a single green band image. Figure 6 and Figure 7 show results of horizontal wave noise removal for the third sample and the fourth sample. We cropped 200×200 patches for visual inspection. Compared with results of wavelet domain deep learning, the results of image domain deep learning show blurred edges and details of images. The wavelet domain deep learning can effectively remove the horizontal wave noise by reconstructing selected band images with preserving high frequency image components. In addition, the results of deep-learning in the wavelet domain with multiband images preserve more edges and details than the results of a single band image, implying that the network can exploit the spatial correlation of multiband images. Astonishingly, the proposed method leads to improved denoising performance by learning the image statistics from the conventional model-based results.

4. CONCLUSION

In this study, we propose a multispectral image denoising method using convolutional neural network in the wavelet domain for the removal of vertical stripe noise and horizontal wave noise. Our experimental results show that the proposed method leads to an improvement by learning the results of conventional model-based results. In addition, it can be observed that the wavelet domain deep learning effectively removes the noise without sacrificing edges and details. Furthermore, the use of multiband images makes the network to exploit spatial correlation between multi-channel images. In the future, a quantitative evaluation of our method is required.

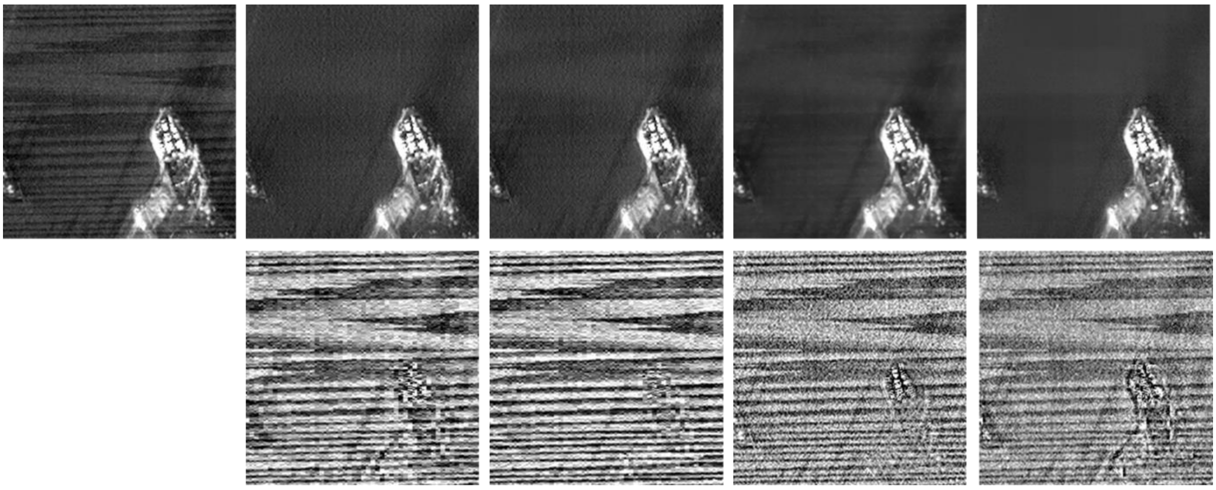


Figure 6. Results of horizontal wave noise removal and difference images for the third sample. (a) Noisy input image, (b) Our results, (c) Results of wavelet domain deep learning with green band, (d) Results of image domain deep learning with green band, (e) Results of conventional model-based reconstruction.

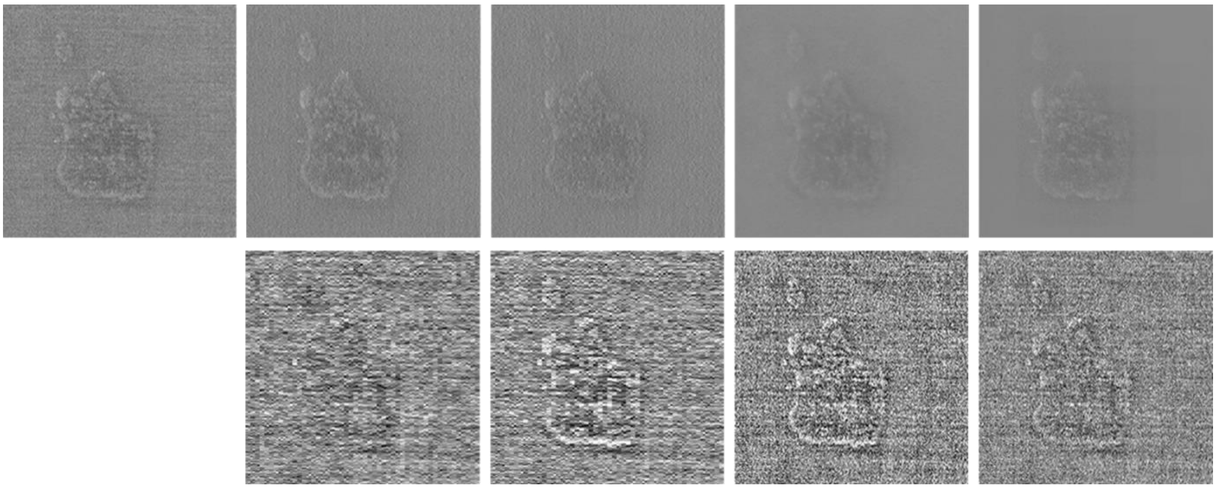


Figure 7. Results of horizontal wave noise removal and difference images for the fourth sample. (a) Noisy input image, (b) Our results, (c) Results of wavelet domain deep learning with green band, (d) Results of image domain deep learning with green band, (e) Results of conventional model-based reconstruction.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

Chang, Y., Yan, L., Fang, H., and Luo, C., 2015. Anisotropic spectral-spatial total variation model for multispectral remote sensing image destriping. IEEE Transactions on Image Processing, 24(6), pp. 1852-1866.

Chang, Y., Yan, L., Fang, H., Zhong, S., and Liao, W., 2018. HSI-DeNet: Hyperspectral image restoration via convolutional neural network. IEEE Transactions on Geoscience and Remote Sensing, 57(2), pp. 667-682.

Liu, W., and Lee, J., 2019. A 3-D Atrous Convolution Neural Network for Hyperspectral Image Denoising. IEEE Transactions on Geoscience and Remote Sensing.

Ronneberger, O., Fischer, P., and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pp. 234-241.

Ulyanov, D., Vedaldi, A., and Lempitsky, V., 2018. Deep image prior. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 9446-9454.

Xie, Q., Zhao, Q., Meng, D., Xu, Z., Gu, S., Zuo, W., and Zhang, L., 2016. Multispectral images denoising by intrinsic tensor sparsity regularization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1692-1700.

Zhang, K., Zuo, W., Chen, Y., Meng, D., and Zhang, L., 2017. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. IEEE Transactions on Image Processing, 26(7), pp. 3142-3155.

Zheng, X., Yuan, Y., and Lu, X., 2018. Hyperspectral Image Denoising by Fusing the Selected Related Bands. IEEE Transactions on Geoscience and Remote Sensing, 57(5), pp. 2596-2609.