Hyperspectral Image Denoising using Superpixels of Mean Band

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Abstract

Denoising is an essential step in the hyperspectral image analysis process. This project proposes a simple process to recover hyperspectral images with moderate levels of Gaussian noise, while keeping most of the details. The proposed method takes a single parameter and uses superpixels to segment the image in small regions of similar pixels. The results obtained were comparable to those produced by bilateral filtering and non-local means algorithms.

1. Introduction

Hyperspectral images are a set of images captured from a scene with multiple wavelengths. Those images tend to be noisy due to the low levels of light captured for each wavelength. That can be an issue if the level of noise interferes on the analysis of the images, reducing the accuracy of classification, diagnostic or detection tasks. Therefore, denoising is a fundamental step of the analysis process.

The motivation for this work was to experiment with a method of simple implementation that could take advantage of the spatial similarity across all frequency bands. If many RGB images of the same scene are captured without changing the camera settings and position, the average of the pixel values of each separate channel (red, green and blue) will result in a clean image. The idea of the proposed method is to apply the same concept to the spectral bands of hyperspectral images and take advantage of the spatial similarity across the image spectra. Certainly, there are aspects of hyperspectral imaging that differ from regular RGB with respect to noise, and it will be discussed on Section 5.

2. Related Work

It is certainly possible to apply the methods that were developed for denoising of single-channel images to each channel of a multispectral or hyperspectral image. However, that would not be taking advantage of the valuable information that comes from the correlation between the image bands. Many papers have taken advantage of such correlation. Fu et al [5] proposed an adaptive spatial-spectral dictionary. Othman and Qian [6] proposed HIS denoising based on wavelets. Liu et al [4] used superpixel-based non-local means. The method presented on this report does not intend to achieve the quality of the results obtained with those state-of-the art methods. Instead, the goal is to achieve satisfactory results with a simplified process, without the computational complexities of more refined methods.

3. Description of the method

The artificially noisy image is obtaining by adding Gaussian noise to the original image.

$$Y = X + n,$$

where X is the original image with M rows, N columns and B frequency bands and n is the added noise with same dimensions as X.

A 2D image with reduced levels of noise is obtained from Y by taking the average of the intensities of all B bands.

$$Y_{avg} = \frac{1}{B}\sum_{b=1}^{B} Y_b$$

The averaged image obtained, Y_{avg}, is significantly less noisy than Y, because the Gaussian noise is considered to be of zero mean. However, the pixel intensities are also averaged and do not match the intensities and contrasts of any of the channels. In order to recover the intensities of each spectral band while keeping the reduced level of noise in Y_{avg}, we can look at small image regions of approximately constant intensity and scale the pixel values in Y_{avg} according to the ratio between the mean pixel value in the region in Y_{avg} and the mean pixel value in the corresponding region of channel Y_b. For each region r_i of the recovered 2D image $X_{r,b}$:

$$r_{i,b} = r_{i,avg} * \frac{\sum_p I_{i,b,p}}{\sum_p I_{i,avg,p}},$$

where $r_{i,b}$ is the region i for band b, $r_{i.avg}$ is the region i in Y_{avg} , $I_{i,b,n}$ is the intensity of pixel p, such that $p \in r_{i,b}$, and $I_{i,avg,n}$ is the intensity of pixel p, such that $p \in r_{i,avg}$.

It is important that the pixels' values of each region considered are approximately constant, so that they can be more accurately represented by the mean of the region. It implies that we want to avoid edges cutting through as much as possible. If we consider the regions to be square windows, it will likely not be the case. Therefore, we propose to segment Y_b in SLIC superpixels [1]. The SLIC clustering algorithm groups the pixels according to their position and intensity. Figure 1 shows two examples of image segmentation using this method.

The process described is shown in Figure 2. The denoised images of each band combine the details and the smoothness from the single-channel average image and the intensities and contrasts from the corresponding noisy Y_b.

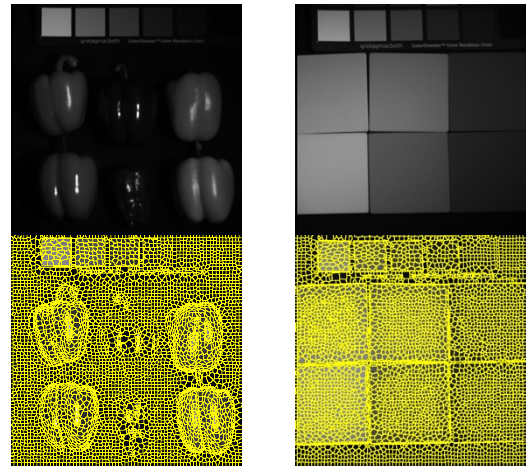


Figure 1 - Superpixels

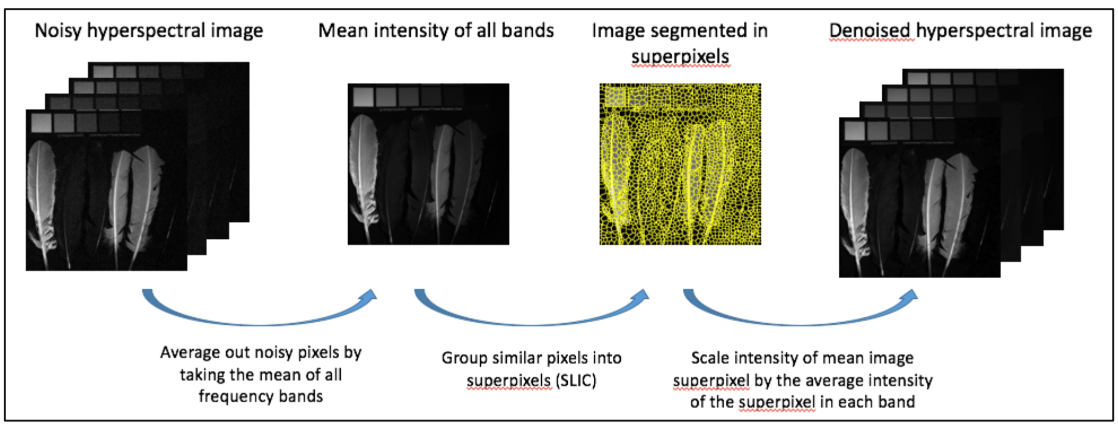


Figure 2 – Proposed method pipeline

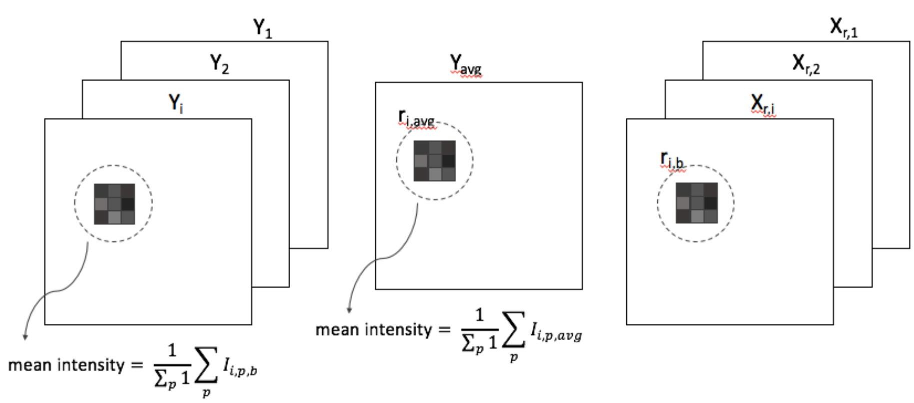


Figure 3 – Mean intensity of pixels in superpixel region are compared and scaled to obtain the pixel values in th superpixel region of the denoised image

4. Results

The method described was tested on several images obtained from the Columbia University Multispectral Image Database [1]. Each image consists of 31 frequency bands, at a spectral resolution of 10 nm. The results were evaluated qualitatively and quantitatively by comparing with results from two efficient and widely used denoising methods for RGB/monochromatic images - bilateral filtering and non-local means. The peak-to-signal ratio (PSNR) was computed for each channel. The PSNR values presented on Figure 4 are the average of the channels.

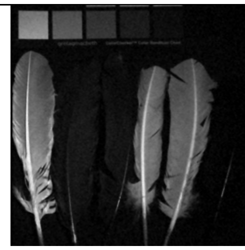
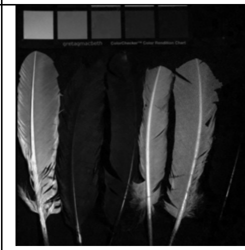
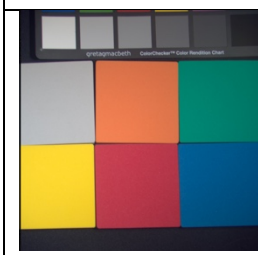
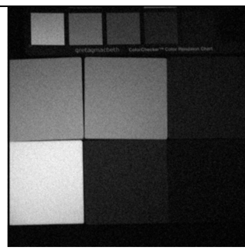
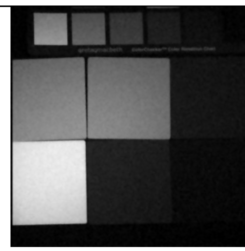
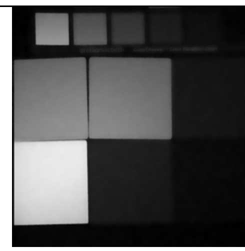
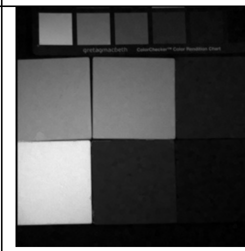
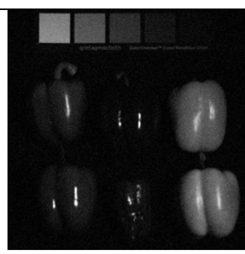
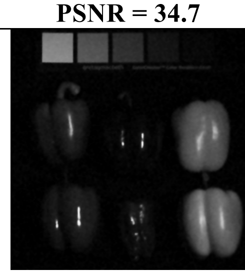
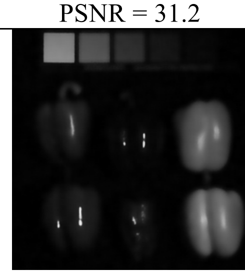
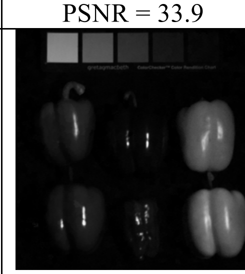
Original image (RGB rendered)	Noisy image	Bilateral filtering	Non-local means	Proposed method
		 PSNR = 34.1	 PSNR = 29.8	 **PSNR = 34.8**
		 **PSNR = 34.7**	 PSNR = 31.2	 PSNR = 33.9
		 **PSNR = 37.7**	 PSNR = 34.5	 PSNR = 35.0
		 PSNR = 26.8	 PSNR = 22.2	 **PSNR = 28.6**

Figure 4 – Results of denoising of images. Column 1 is the RGB rendered original image, column 2 is the noise image, column 3 is the result of a single channel with bilateral filtering, column 3 is the result of a single channel with non-local means and column 5 is the result of a single channel with the proposed method.

5. Discussion

The results obtained with the proposed method are comparable to those from bilateral filtering and non-local means. The denoised images preserve details from the original image better than the other methods. In fact, all details are preserved in this process. Another advantage of this method is how simple it is to be implemented. Compared to non-local means, the calculations are performed much faster. In addition, there is only one parameter to be adjusted, which is the number n_{sp} of superpixels for the image segmentation.

The quality of the recovered image is highly dependent on the choice of the single parameter. Selecting a value that is too low will result in large regions r_i and, consequently, it will not be possible to scale the contrasts properly. On the other hand, if the value selected for n is too high, the mean intensity of the very small regions will be too much affected by the noisy pixels. For the dataset tested, the optimum value of n was around 3000 superpixels.

Results are also dependent on the noise level. Figure 5 shows the denoised 580nm band for different levels of noise. We can observe that the proposed method works better when noise level is not two high. That is because, when considering the mean intensity of the superpixel, the noisy pixels will weigh in a lot more.

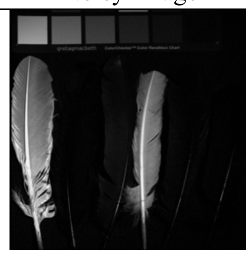
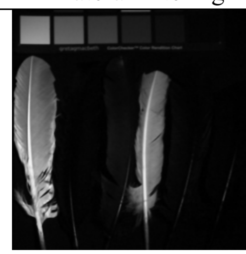
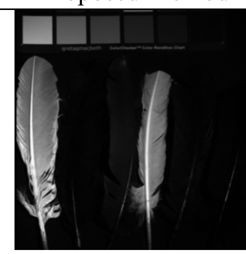
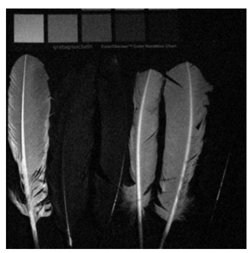
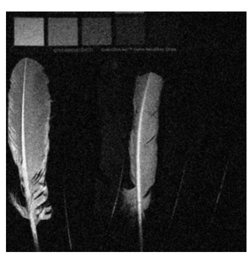
σ_{noise}	Noisy Image	Bilateral filtering	Proposed Method
0.01		 PSNR = 37.1	 **PSNR = 38.0**
0.05		 PSNR = 34.1	 **PSNR = 34.8**
0.1		 **PSNR = 27.7**	 PSNR = 23.6

Figure 5 – Comparison of results between proposed method and bilateral filtering for different levels of noise

It should be pointed out that, in hyperspectral images, the noise level is not the same for all wavelengths. Therefore, averaging all monochromatic images together may not be really efficient to reduce it. However, the goal of computing the average is only to obtain a clean image. Therefore, the average does not need to be computed from all frequency bands. It can be computed from the range of wavelengths with similar levels of noise. And the number of bands to be averaged should still be enough to nearly cancel out the noisy pixels.

6. Conclusion

This work demonstrated how the spatial similarity across spectral bands can be used to reduce low levels of noise in hyperspectral images with simple calculations, while keeping a very good detail resolution.

References

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