PANSHARPENING USING TOTAL VARIATION REGULARIZATION

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ABSTRACT

In remote sensing, pansharpening refers to the technique that combines the complementary spectral and spatial resolution characteristics of a multispectral image and a panchromatic image, with the objective to generate a high-resolution color image. This paper presents a new pansharpening method based on the minimization of a variant of total variation. We consider the fusion problem as the colorization of each pixel in the panchromatic image. A new term concerning the gradient of the panchromatic image is introduced in the functional of total variation so as to preserve edges. Experimental results on IKONOS satellite images demonstrate the effectiveness of the proposed method.

***Index Terms*—** Pansharpening, image fusion, multispectral images, total variation

1. INTRODUCTION

Pansharpening has recently attracted a lot of research interest for its ability to improve the spatial resolution of multispectral (MS) images with the help of panchromatic (Pan) image. MS and Pan images provided by spaceborne sensors present different characteristics. The MS images have a high spectral resolution but low spatial resolution whereas the Pan image has a low spectral resolution but high spatial resolution. In many environmental applications it has been shown that images with both high spectral and spatial resolutions may be beneficial [1, 2, 3].

Classical pansharpening techniques can be divided into two categories: the component substitution methods [4, 5, 6, 7] and the multiresolution-analysis methods [8, 9]. The component substitution methods first make use of a projection of the upsampled MS images to obtain a better representation of which one component contains most of the image structures. The fusion occurs then by the substitution of certain significant structures by those of the Pan image. The multiresolution-analysis methods rely on the injection of the high frequency infomation of the Pan image into the upscaled MS image and they often employ spatial filters, such as the Discrete Wavelet Transforms (DWT) to extract the high spatial frequency information from the Pan image.

Recently the high performance of variational appoaches for various image processing applications has given rise to a new branch of research for pansharpening. We may cite the work of Ballester *et al.* [10], named by P+XS method, and Möller *et al.* [11], named by VWP for Variational Wavelet Pansharpening. The P+XS method introduces the geometry information of the Pan image by aligning all level lines of the Pan image with each multispectral band. In order to get the spectral information for the fused image, it makes the assumption that the Pan image can be approximated as a linear combination of the high resolution multispectral bands. The VWP method does not follow the same assumption of P+XS. It combines ideas of wavelet fusion for a higher spectral quality and P+XS for producing similar geometry information. Both P+XS and VWP rely on the minimization of a certain energy functional that shares properties with the total variation. In this paper, we propose a variational approach for pansharpening based on a direct minimization of a variant of total variation.

The total variation is initially introduced in image processing for the regularization of inverse problems [12]. In recent years, total variation based methods have had great success in many applications: image restoration, denoising, inpainting and so on. They have shown great ability to preserve the sharp discontinuties such as edges and object contours. In this paper, we focus our attention on a variant of the total variation for pansharpening. The process of pansharpening can be considered as the colorization of the pixels in the panchromatic image. We introduce a term concerning the gradient of the panchromatic image in the new function of total variation so as to preserve important geometric and structural information for the fused image.

The outline of this paper is as follows. In Section 2, we detail the proposed pansharpening method based on a new function of total variation. Section 3 presents some experimental results obtained on IKONOS satellite images. Finally we conclude the paper and propose several future working directions in Section 4.

2. THE PROPOSED METHOD

We first formalize the problem. Suppose that $x[\mathbf{k}]$ is the pixel value of an image x at location $\mathbf{k} = [k_1, k_2]^{\mathrm{T}} \in \mathbb{Z}^2$.

(a) (b) (c)

Fig. 1. The fused image when using different values of α: (a) $\alpha = 0.1$; (b) $\alpha = 1$; (c) $\alpha = 100$.

p is the Pan image at high resolution and $u_1, u_2, \ldots, u_N$ are the multispectral images at low resolution, where N is the number of bands. More precisely the multispectral image $\mathbf{u}$ can be seen as a vector-valued image with $\mathbf{u}[\mathbf{k}] = [u_1[\mathbf{k}], u_2[\mathbf{k}], \ldots, u_N[\mathbf{k}]]^{\mathrm{T}} \in \mathbb{R}^N$, $\forall \mathbf{k} \in \mathbb{Z}^2$. $v_1, v_2, \ldots, v_N$ are the fused multispectral images at the same high resolution as the Pan image p. We introduce the reduction operator $\mathcal{R}$ which down-scales a high-resolution image into a low-resolution one. If the scaling factor m is an integer, $\mathcal{R}$ is simply a convolution with a lowpass filter h followed by down-sampling, that is $\mathcal{R}x[\mathbf{k}] = (x * h)[m\mathbf{k}]$, $\forall \mathbf{k} \in \mathbb{Z}^2$. Then our only assumption is that

$$u_i = \mathcal{R}v_i + \text{i.i.d. centered noise}, \quad \forall i = 1, 2, \ldots, N. \quad (1)$$

We regularize the obviously ill-posed inverse problem of pansharpening and fomulate it as

$$\begin{cases} \text{minimize}_{\mathbf{v}} & \|\mathbf{v}, p\|_{TV} \\ \text{subject to:} & \frac{1}{M} \|\mathcal{R}v_i - u_i\|_{\ell_2}^2 \leq \epsilon, \quad \forall i = 1, 2, \ldots, N \end{cases} \quad (2)$$

where M is the total number of pixels in image u_i and $\epsilon \geq 0$ controls the fit to the data and should be chosen close to the noise variance, according to [13]. $\|\mathbf{v}, p\|_{TV}$ is an apropriate total variation that we define based on the gradient of Pan image p and the fused image $\mathbf{v}$:

$$\|\mathbf{v}, p\|_{TV} = \sum_{\mathbf{k} \in \mathbb{Z}^2} \sqrt{\alpha^2 \|\nabla p[\mathbf{k}]\|^2 + \|\nabla v_1[\mathbf{k}]\|^2 + \cdots + \|\nabla v_N[\mathbf{k}]\|^2}, \quad (3)$$

where the gradient of each pixel in the image is calculated by discrete backward differences:

$$\|\nabla x[\mathbf{k}]\|^2 = (x[\mathbf{k}] - x[k_1 - 1, k_2])^2 + (x[\mathbf{k}] - x[k_1, k_2 - 1])^2, \quad (4)$$

with the application of Neumann boundary conditions, that is, a finite difference across the boundary is set to zero.

It is noted that in the new function of total variation in Eq. (3), α is a parameter that controls the importance of the geometric information of the pan image in the fused image. A small value of α will lead to similar results as the original total variation method whereas a big value of α enforces more emphasis on the information of the pan image.

An alternative formulation to Eq. (2) is the following:

$$\underset{\mathbf{v}}{\text{minimize}} \, \|\mathbf{v}, p\|_{TV} + \lambda \sum_{i=1}^{N} \|\mathcal{R}v_i - u_i\|_{\ell_2}^2 , \quad (5)$$

where $\lambda > 0$ is the regularization parameter. The problems (2) and (5) are equivalent, in the sense that for every $\epsilon > 0$, there exists $\lambda > 0$, and conversely, such that both problems yield the same solution. We solve the problem by the first-order primal-dual algorithm proposed in [14].

3. EXPERIMENTS AND RESULTS

In this section we present briefly several experimental results on IKONOS satellite images. The MS image is at 4-m resolution with four bands (Red, Green, Blue and Nir) while the Pan image is at 1-m resolution. Test images were selected from images taken over the city of Xuzhou in China.

3.1. Influence of α

As mentioned in Section 2, the parameter α in Eq. (3) plays an important role in the proposed pansharpening algorithm. Experiments were first conducted to study the influence of this parameter. Figure 1 presents an example of the fused image when using different α values: $\alpha = 0.1, 1, 100$. We can see that a small value of $\alpha = 0.1$ results in a blurred image similar to the conventional total varition method without the gradient term of the Pan image. A large value of $\alpha = 100$ makes the pansharpening procedure pay too much attention on the Pan image and thus produces an image with a severe distortion of spectral information. We also see that for an appropriate value of α, the proposed method gives quite satisfactory result, as shown in Fig. 1. (b). Therefore, in the following we set $\alpha = 1$.

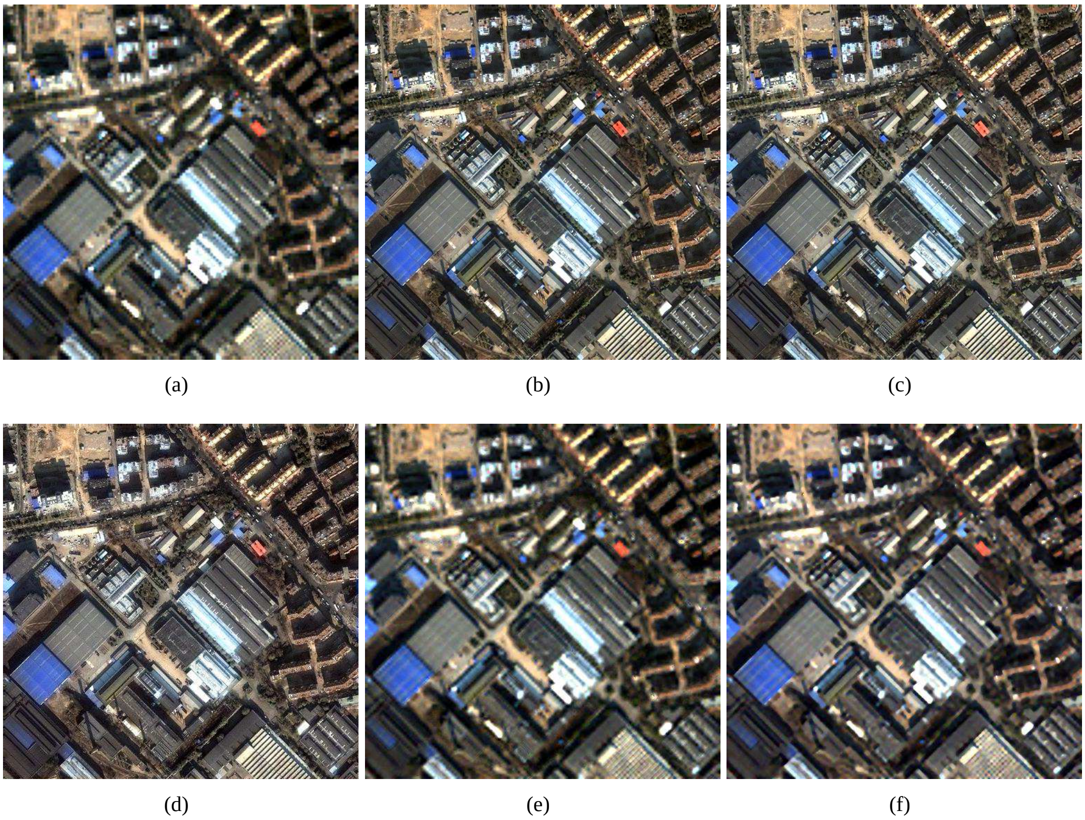

Fig. 2. Comparison of different pansharpening methods. The resulting image is represented as a true-color combination of the Red, Green and Blue bands. The scene presented is of size 512×512, at 1-m resolution. (a) MS image obtained by a bicubic interpolation. (b) PCA fused image [4]. (c) GS fused image [5]. (d) ATWT fused image [9]. (e) P+XS fused image [10]. (f) Fused image using the proposed method, $\alpha = 1$ and $\epsilon = 10^{-4}$.

3.2. Comparison to other pansharpening methods

The proposed method was compared with four classical pansharpening techniques: PCA [4], GS [5], ATWT [9] and the variational method P+XS [10]. Without *a priori* information about the satellite model, for the P+XS method, we assume that the Pan image is given by a linear combination with equal weights of each high-resolution multispectral band. The parameter ϵ in Eq. (2) of our method is set as 10^{-4}. Figure 2 shows the results of different methods, in form of color images as a combination of the Red, Green and Blue bands. The upscaled MS image produced by bicubic interpolation is also given. It can be observed that both the P+XS method and the proposed method have the best spectral quality. Moreover, it is difficult to assess the spatial quality just by looking at the fused images.

As we do not have a reference high-resolution MS image, traditional quality metrics, i.e. SAM [15], ERGAS [16], Q4 [15] cannot be used. Therefore we adopt the QNR metric proposed in [17] to examine the quality of the fused image. The QNR can provide three indices: spectral distortion (D_λ), spatial distortion (D_S) and total quality (QNR). Table 1 presents the results of different pansharpening methods, which confirm the above visual inspection of the high spectral quality of the two variational methods. In particular, the proposed method has a much higher spatial quality than the other methods. For the overall performance, we can see that our method performs the best.

4. CONCLUSION AND FUTURE WORK

This paper presents a new variational approach for pansharpening. The novelty lies in the direct minimization of a variant of total variation function, without resorting to the assumption that the Pan image can be written as a linear combination of the multispectral bands and without conducting multiresolution analysis. Experimental results demonstrate the effectiveness and potential of the proposed method. In particular, the method has a high spatial quality. The extension of this work to other satellite images, such as 8-band multispectral images and hyperspectral images are currently investigated.

Table 1. Quantitative evaluation of the high-resolution MS images produced by different pansharpening methods

Method	QNR	Spectral distortion D_λ	Spatial distortion D_S
Ideal Value	1	0	0
PCA [4]	0.729	0.104	0.186
GS [5]	0.718	0.0969	0.205
ATWT [9]	0.829	0.0263	0.149
P+XS [10]	0.917	**0.00107**	0.0819
The proposed method	**0.991**	0.00167	**0.00778**

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