Performance Evaluation for Pan-sharpening Techniques

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Abstract — **Image fusion is to combine multiple images from the same sensor or different sensors into composite products, through which more information than that of individual input images can be revealed. As an example of image fusion, pan-sharpening is a process of transforming a set of low-spatial-resolution multispectral images to high-spatial-resolution images, by fusing a co-registered fine-spatial-resolution panchromatic image. In the fused output, spectral signatures of a multispectral image and spatial features of the panchromatic image, as the best attributes of both inputs, are almost retained. The spatially enhanced image is visually appealing. But spectral distortion may be incurred during this procedure. Currently performance evaluation is focused on colorful spatial looking. In this paper we will investigate the application of unsupervised linear unmixing to jointly evaluate the spatial and spectral fidelity of a pan-sharpened image.**

Keywords: pan-sharpening; performance evaluation; multispectral image; linear mixture model; unsupervised linear unmixing; abundance estimation.

I. INTRODUCTION

Pan-sharpening is a typical approach to integrating the geometric detail of a high-resolution panchromatic image and the spectral information of a low-resolution multispectral image to produce a high-resolution multispectral image. Many pan-sharpening methods have been developed. These methods can be divided into four major categories: intensity-hue-saturation (IHS) transform based methods, principal component analysis (PCA) based methods, arithmetic combination based methods, and wavelet transform based methods. Each of them has some advantages and limitations [1-6].

It is necessary to quantitatively evaluate the performance of different pan-sharpening methods. Current performance evaluation is mainly focused on image spatial looking. For instance, frequently used metrics for spatial similarity are mean square error (MSE), root mean square error (RMSE), correlation coefficient, entropy, etc. When spatial resolution is improved, there is tradeoff for spectral fidelity. So it is better to jointly evaluate both spatial and spectral information. A new quality index for this purpose is proposed based on the theory of hypercomplex numbers, or quaternions, in [6]. Unfortunately, it is suitable to multispectral images with no more than four bands.

We will propose a new evaluation method based on linear unmixing. It is well known that the rough spatial resolution of a remote sensing image makes different materials be present in the area covered by a single pixel. The linear mixture model says that a pixel reflectance in a visible-near infrared multispectral or hyperspectral image is the linear mixture from all independent pure materials (i.e., endmembers) present in an image scene. Let L be the number of spectral bands and $\mathbf{r}$ an $L\times 1$ column pixel vector. Assume that there are P endmembers present in an image scene, which construct an $L\times P$ signature matrix $\mathbf{M}=[\mathbf{m}_1\mathbf{m}_2\cdots\mathbf{m}_P]$, where $\mathbf{m}_j$ represents the j-th endmember. Assume that $\boldsymbol{\alpha}=(\alpha_1\alpha_2\cdots\alpha_P)^T$ is a $P\times 1$ abundance vector associated with $\mathbf{r}$, where α_j denotes the abundance fraction of the $\mathbf{m}_j$ in $\mathbf{r}$. In the linear mixture model, $\mathbf{r}$ is considered as the linear mixture of $\mathbf{m}_1$, $\mathbf{m}_2$, …, $\mathbf{m}_P$ as

$$\mathbf{r}=\mathbf{M}\boldsymbol{\alpha}+\mathbf{n} \tag{1}$$

where $\mathbf{n}$ is the noise term. If $\mathbf{M}$ is known, $\boldsymbol{\alpha}$ can be estimated by minimizing the following error

$$\min_{\boldsymbol{\alpha}}(\mathbf{r}-\mathbf{M}\boldsymbol{\alpha})^T(\mathbf{r}-\mathbf{M}\boldsymbol{\alpha}). \tag{2}$$

In addition, two constraints are generally imposed on $\boldsymbol{\alpha}$: abundance sum-to-one constraint, i.e., $\sum_{p=1}^{P}\alpha_p=1$, and abundance non-negativity constraint, i.e., $\alpha_p\geq 0$ for all $1\leq p\leq P$. There is no closed-form solution to such a constrained linear unmixing problem. So an iterative method generally is used.

II. PAN-SHARPENING METHODS

Four different types of pan-sharpening methods are briefly reviewed here.

Intensity-hue-saturation transform based methods

Three bands of a multispectral image are considered as in a color image. The intensity-hue-saturation (IHS) transform is conducted, which separates the intensity information from the color information (hue and saturation). Then the panchromatic image replaces the intensity image. Pan-sharpened image can be generated by inverse IHS transform. The drawback of this method is that it is only suitable to a three-band multispectral image. Otherwise, we have to select three bands from all original bands for pan-sharpening.

Principal component analysis based methods

Principal component analysis (PCA) is another commonly used technique for pan-sharpening. PCA is applied to the original image. Then the first principle component (PC) image is replaced by the panchromatic image. Here we assume that the first PC image with largest variance contains the major information in the original image. However, we know that data information is distributed among several PCs. So obviously this method brings about spectral distortion. However, it is suitable to an image with any number of bands.

Arithmetic combination based methods

The most famous technique in this category is Brovey transform, which is actually a band-multiplicative method. For the *i*-th band, it is generated by: Fused Band *i* = Pan * Band *i* / (Band 1 + Band 2 +… + Band *N*). The computation is on pixel-by-pixel basis.

Wavelet based methods

A wavelet based method includes three steps: forward transform, coefficient combination, and backward transform. There are different ways to fuse the wavelet coefficients of the original image and panchromatic image. For example, one fusion rule takes the vertical, horizontal, and detail coefficients from the panchromatic image, and takes the approximation coefficients from the multispectral image. Another rule takes the average of vertical, horizontal, and diagonal coefficients of the panchromatic and multispectral images, and takes the approximation coefficients from the multispectral image. We can also compare the vertical, horizontal, and diagonal coefficients from panchromatic and multispectral images and pick the largest magnitudes as the fused wavelet coefficients.

Hybird methods can be developed by the combination of different types of techniques to achieve the lowest spectral distortion.

III. Linear unmixing based performance evaluation

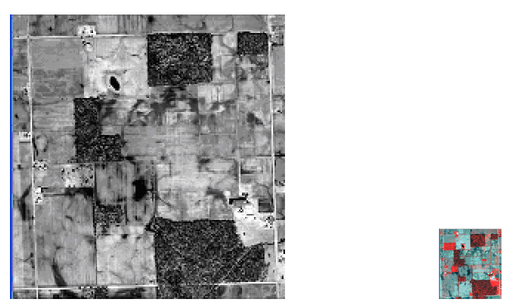
The evaluation method we propose to use is based on linear unmixing method. Both endmember signatures and their abundance distributions will be estimated for the original image and pan-sharpened image. Then two sets of endmember signatures are compared to evaluate the spectral information distortion, while two sets of fractional abundance images are compared to evaluate the spatial similarity using a method, such as correlation coefficient.

Because pixel spectral signatures are changed during the sharpening process, an unsupervised method is used to estimate the endmember signatures in $\mathbf{M}$ as well as their abundances. The unsupervised fully constrained least squares linear unmixing (UFCLSLU) algorithm is used for this purpose [7]. Initially, any arbitrary pixel vector can be selected as an initial denoted by $\mathbf{m}_0$. However, a good choice may be a pixel vector with the maximum length. It is assumed that all other pixel vectors are pure pixels made up of $\mathbf{m}_0$ with 100% abundance. A pixel vector that has the largest least square error (LSE) between itself and $\mathbf{m}_0$ is found and selected as a first endmember $\mathbf{m}_1$. Because the LSE between $\mathbf{m}_0$ and $\mathbf{m}_1$ is the largest, it can be expected that $\mathbf{m}_1$ is most distinct from $\mathbf{m}_0$. Then $\mathbf{M} = [\mathbf{m}_0\mathbf{m}_1]$ is formed. The FCLSLU algorithm is used to estimate the abundance fractions for $\mathbf{m}_0$ and $\mathbf{m}_1$, denoted by $\hat{\alpha}_0^{(1)}(\mathbf{r})$ and $\hat{\alpha}_1^{(1)}(\mathbf{r})$ for each pixel $\mathbf{r}$ respectively as the estimates from the first iteration. Now an optimal constrained linear mixture of $\mathbf{m}_0$ and $\mathbf{m}_1$, $\hat{\alpha}_0^{(1)}(\mathbf{r})\mathbf{m}_0 + \hat{\alpha}_1^{(1)}(\mathbf{r})\mathbf{m}_1$, is computed to approximate the $\mathbf{r}$. Then the LSE between $\mathbf{r}$ and this estimated linear mixture is calculated for all image pixel vectors $\mathbf{r}$. Once again a pixel vector that yields the largest LSE will be selected to be a second object pixel vector $\mathbf{m}_2$. As expected, such a selected object pixel is the most dissimilar to $\mathbf{m}_0$ and $\mathbf{m}_1$. The same procedure with $\mathbf{M} = [\mathbf{m}_0\mathbf{m}_1\mathbf{m}_2]$ is repeated until the resulting LSE is below a prescribed error threshold η or enough endmembers are generated.

Before this processing, the size of an original image is expanded to the same size of the panchromatic image using an interpolation method, such as bilinear interpolation.

IV. Experiment

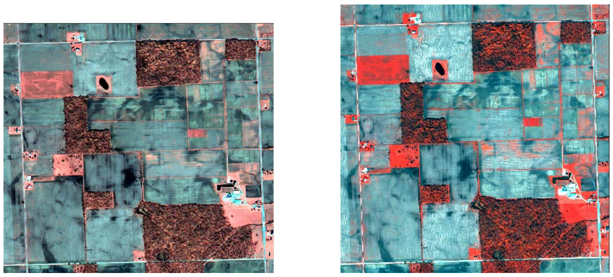
The Quickbird multispectral and panchromatic images about Davis-Purdue Agricultural Center (DPAC) were used in the experiment. As shown in Figure 1, the dimension of the panchromatic image is 2600×2600, while the multispectral image is of size 650× 650 with four bands (blue, green, red, and near infrared). Their spatial resolutions are 2.6m and 0.75m, respectively.



Pan image Multispectral image

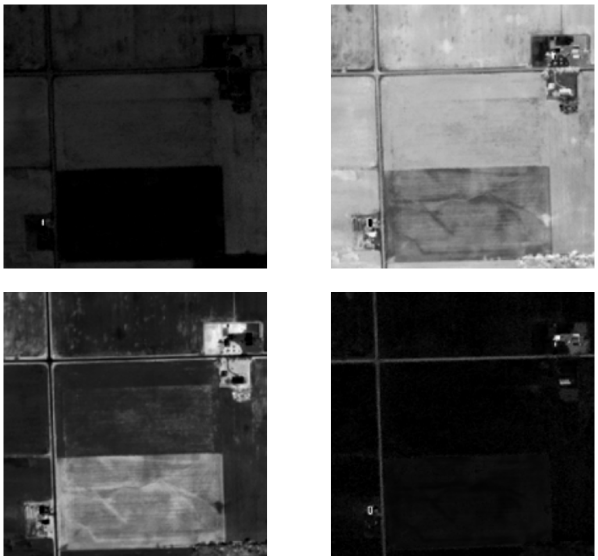
Figure 1. Original Panchromatic and Multispectral imags.

Figure 2 lists the pan-sharpened images using PCA and wavelet methods. Here, the color-infrared composite images are displayed. Compared to the original image in Figure 1, we can see that color (spectral) distortion is obviously in the PCA-based pan-sharpened image, while colors in the one from wavelet method seem more faithful.

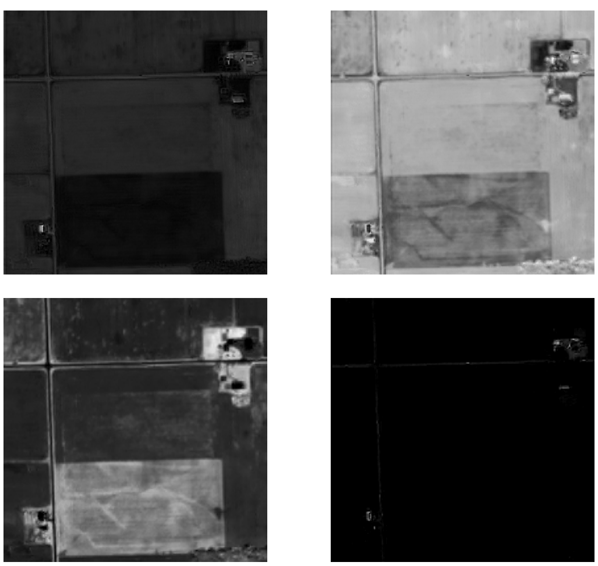


PCA Wavelet

Figure 2. Fusion results using four methods.



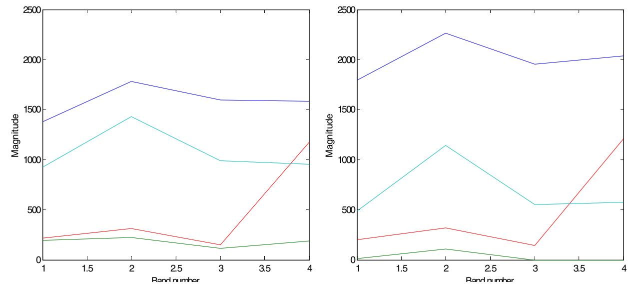
From the original image (after bilinear interpolation)



From the pan-sharpened image (Wavelet)

Figure 3. Fractional Abundance Images

Then four endmemebers and their fractional abundance images were estimated, as shown in Figure 3 and 4 (only those from the original image and wavelet-based pan-sharpened images are presented here). Corresponding abundance images were compared, and correlation coeffiencts were calculated. Spectral information was compared via correlation coefficient between endmembers of the same materials in different images. As listed in Table 1, spatial and spectral correlations between the wavelet-based pan-sharpened image and orignal image are higher than the PCA-based pan-sharpened image.



For the original image For the pan-sharpened image

Figure 4. Four endmemeber signatures

Table 1. Averaged spatial and spectral correlation coefficients

	Spatial	Spectral
PCA	0.7540	0.8598
Wavelet	0.8431	0.9070

V. Conclusion

We propose to use unsupervised linear unmixing method for evaluation of pan-sharpened images. Instead of working on individual band images, endmembers and their fractional abundance components from the pan-sharpened image and orignal image are compared. Such an application-oriented joint comparison can effectively compare both spatial and spectral information. However, its performance needs further investigation.

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