Comparison of Nine Hyperspectral Pansharpening Methods

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1 Abstract

Pansharpening first aims at fusing a panchromatic image with a multispectral image to generate an image with the high spatial resolution of the former and the spectral resolution of the latter. In the last decade many algorithms have been presented in the literature for pansharpening using multispectral data. With the increasing availability of hyperspectral systems these methods are now extending to hyperspectral images. In this work, we attempt to compare new pansharpening techniques designed for hyperspectral data with some of the state of the art methods for multispectral pansharpening, which have been adapted for hyperspectral data. Nine methods from different classes are analysed: component substitution, multiresolution analysis, hybrid, Bayesian and matrix decomposition approaches. These techniques are evaluated with the Wald's Procol on one dataset to characterize their performances and their robustness.

2 Introduction

In the design of optical remote sensing, tradeoffs are searched between spatial and spectral resolutions and signal-to-noise ratio (SNR). For this reason, optical systems can provide data with a high spatial resolution but a low number of spectral bands or have a high spectral resolution but reduced spatial resolution. To enhance the spatial resolution of multispectral data, several methods have been proposed in the literature under the name of pansharpening. These methods consist of merging a panchromatic image with a multispectral image to obtain a final enhanced image with both high spatial and spectral resolutions.

A taxonomy of pansharpening methods can be found in the literature [1]. They can be mainly divided into two classes: the component substitution (CS) and the multiresolution analysis (MRA). The former approach relies on the substitution of a component (e.g., obtained by a spectral transformation of the data) of the multispectral (subsequently denoted as MS) image by the panchromatic (subsequently denoted as PAN) image. This family contains algorithms such as principal component analysis (PCA) [2] and Gram-Schmidt (GS) spectral sharpening [3]. The MRA approach is based on the injection of spatial details, which are obtained through a multiscale decomposition of the PAN image into the MS data. The spatial details can be extracted according to several modalities of MRA: Laplacian pyramid [4], smoothing filter-based intensity modulation (SFIM) [5]. Hybrid methods have been also proposed, which use component substitution and multiscale decomposition such as guided filter PCA (GFPCA) [6]. With the increasing availability of hyperspectral systems these methods are now extending to the fusion of hyperspectral and panchromatic images. Pansharpening of hyperspectral (subsequently denoted as HS) images is still an open issue and very few methods are presented in the literature to address this specific problem.

The main advantage of HS data with respect to MS data is the more accurate spectral information necessary for applications such as change detection, object recognition, scene interpretation and improvement of classification maps. A large part of existing methods designed for HS pansharpening are originally designed for the fusion of MS and HS data, where the MS data represents the high spatial resolution image. HS pansharpening in this case can be seen as a particular case where the MS image is composed of one band and thus reduces to a PAN image. These methods can be divided into two classes : Bayesian methods [7] [8] and matrix decomposition based methods [9]. However doing pansharpening with HS data is more complex than doing it with MS data.

Firstly, whereas PAN and MS data are acquired almost in the same spectral range it is generally not the case with HS data. The spectral range for an HS image is mainly wider than the one for a PAN image. Usually the PAN spectral range is related to the visible spectral domain [0.4 - 0.8 μm] and the HS range can cover the visible to the shortwave infrared (SWIR) spectral domains [0.4-2.5] μm with the spectrum part 0.8-2.5 μm which is not covered by the PAN domain. So the main difficulty here is to define a fusion model working in the spectral domain not covered by both PAN and HS data where information is missing.

Secondly, spectral distortion is introduced when using methods originally designed for MS pansharpening since some features are not visible in both PAN and each MS spectral band. This may become more important when dealing with HS images since the number of spectral bands is higher than in a MS image.

In addition, working with HS images instead of MS image increased computational burden. The scale ratio between PAN and HS images could not be a power of two (dyadic approaches cannot be used) and HS and PAN sensors are often on-board of different satellite platforms.

To the best of the authors' knowledge, there is currently no study comparing different fusion methods for HS data, particularly on datasets where the spectral domain of the HS image is larger than the PAN one. This work aims at addressing this specific issue.

3 Quality Assessment of fusion products

Quality measures have been defined in order to determine the similarity between different images, e.g., by ensuring both consistency and synthesis properties of Wald's protocol [10]. These measures can be generally classified into different categories depending on a spatial, spectral or global aspect (one measure for the preservation of both spatial and spectral information preservation). This paper is limited to the most widely used quality measures. In this section, the reference and fused images are denoted as A and B.

3.1 Spatial measure

The *cross correlation (CC)* characterizes geometric distortion and is mainly a spatial criteria defined as

$$\mathrm{CC}(A,B) = \frac{\sum_i (A_i - \mu_A)(B_i - \mu_B)}{\sqrt{\sum_i (A_i - \mu_A)^2 \sum_i (B_i - \mu_B)^2}} \tag{1}$$

where μ_A and μ_B are the means of the signals A and B, where the sum is computed for all the elements of each signal. The cross correlation CC is computed for each bands of the HS image and a global criteria is computed by averaging all the value of CC. The ideal value of CC is 1.

3.2 Spectral measures

The *spectral angle mapper (SAM)* computes the angle between the corresponding pixels of the fused and reference images in the space defined by assigning each spectral band to a coordinate axis. The SAM computes the distance between two spectral signatures and thus defines an error from a spectral point of view. It is an important spectral measure (particularly if the fused image is used for classification) defined as

$$\mathrm{SAM}(A,B) = \arccos\left(\frac{\langle A,B\rangle}{\|A\|\|B\|}\right) \tag{2}$$

in which $\langle .,. \rangle$ denotes the scalar product (or inner product) and $\|.\|$ is the associated ℓ_2 norm. The global value of SAM for the whole image is obtained by averaging the SAM values of all the image pixels. The optimal value of the SAM is 0.

The *root mean square error (RMSE)* measures a spectral distortion by computing the difference between the image A and B. The RMSE between image A and B is define as

$$\mathrm{RMSE} = \sqrt{E(A-B)^2} \tag{3}$$

in which the expected value is approximated by a spatial average. The ideal value of RMSE is 0.

3.3 Global

The *relative dimensionless global error in synthesis (ERGAS)* is an error measure that offers a global indication of the quality of a fused product. It is defined by:

$$\text{ERGAS} = \frac{100}{R}\sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(\frac{RMSE(l)}{\mu(l)}\right)^2} \tag{4}$$

where R is the ratio between the PAN and HS images (ratio is defined as $\frac{HS spatial resolution}{PAN spatial resolution}$, $\mu(l)$ is the mean of the lth band, and L is the number of bands. The ideal value of ERGAS is 0 and a low value of ERGAS indicates similarity between the two images A and B.

4 Experimental Results

The dataset represents a rural area from Camargue (France) with different kind of crops. The image dimensions are 500*500 pixels for the PAN image with a spatial resolution of 4 m and 125*125 pixels for the HS image with a spatial resolution of 16 m, which mean a spatial resolution ratio of 4 between the two images. It is acquired by the airborn hyperspectral instrument HyMap (Hyperspectral Mapper) in 2007. The hyperspectral instrument is characterized by 125 spectral bands in the reflective domain [0.4 μm - 2.5 μm].

Spectral bands related to water absorption and noise are removed before the fusion. This is a semi synthetic dataset, PAN image is simulated with the original HS image and the HS image for the fusion is also simulated by degrading the original HS image. This is down by filtering the original HS image with Kernel Gaussian followed by a downsampling. The original HS image is kept as the reference and will be used for quality assessment. Note that the dataset considered in this work is in spectral luminance (nearest to the sensor without pre-processing) and is supposed to be correctly registered (no registration error will be considered in this paper).

Results of the quality measures is presented in Table.1 and results of fusion products from an extract of the dataset is shown Fig. 1 .

TABLE 1: Quality measures

method	CC	SAM	RMSE	ERGAS
SFIM	0.953635	3.35615	390.994	3.11817
MTF GLP HPM	0.947264	3.34547	371.217	2.99524
GSA	0.959663	3.19620	371.163	3.06694
PCA	0.867211	4.59498	566.927	4.53938
GFPCA	0.907359	3.73884	536.801	4.18933
CNMF	0.948618	3.53197	390.680	3.35629
Bayesian Sparse	0.969430	2.97138	340.111	2.82226
HySure	0.963243	3.08586	350.558	3.01887

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Fig. 1: Details of original and fused Camargue dataset HS image. (a) reference image, (b) HS image interpolated, (c) SFIM, (d) MTF GLP HPM, (e) GSA, (f) PCA, (g) GFPCA, (h) CNMF, (i) Bayesian Sparse, (j) HySure