PIXEL LEVEL FUSION METHODS FOR REMOTE SENSING IMAGES: A CURRENT REVIEW

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ABSTRACT:

Image fusion is capable of integrating different imagery to produce more information than can be derived from a single sensor. So far, many pixel level fusion methods for remote sensing images have been presented, in which the lower resolution multispectral image's structural and textural details are enhanced by adopting the higher resolution panchromatic image corresponding to the multispectral image. For this reason, it is also called pansharpening. In this paper we will list current situation of pixel level image fusion by dividing those methods into three categories, i.e., component substitution technique, modulation based technique and multi-resolution analysis based technique according to fusion mechanism. Also, the properties of the three categories for applications are discussed.

1. INTRODUCTION

Data fusion is capable of integrating different imagery data to produce more information than can that be derived from a single sensor. There are at least two limitations accounting for demanding pixel level image fusion technology. One is that the received energy of multispectral sensor for each band is limited because of the narrow wavelength range of the multispectral band. In general, the values of Ground projected Instantaneous Field Of View (GIFOV) (Schowengerdt, 1997) of multispectral bands are larger than those of the panchromatic bands. In order to obtain smaller GIFOV value in relatively narrow wavelength range, image fusion technology is demanded to enhance structural and spatial details. The other is that the capability transmitting the acquired data to the ground is restricted. However, at present the transmission equipments of remote sensing system can not address the requirements. Henceforth, after ground stations receives multispectral images containing relatively less data, the combination of multispectral bands with the higher resolution panchromatic band can resolve the problem to some extent. So far, many pixel-level fusion methods for remote sensing image have been presented where the multispectral image's structural and textural details are enhanced by adopting the higher resolution.

In the recent literature, IEEE Transaction on Geoscience and Remote Sensing had published a special issue on data fusion in May 2008, which includes several new developments for current situation of image fusion (Gamba and Chanussot, 2008). In January 2006, the Data Fusion Committee of the IEEE Geoscience and Remote Sensing Society launched a public contest for pansharpening algorithms (Alparone, et al., 2007), which aimed to identify the ones that perform best. The fusion results of eight algorithms (GLP-CBD, AWLP, GIHS-GA, WiSpeR, FSRF, UNB-Pansharp, WSIS, GIHS-TP) from worldwide participants were assessed both visually and quantitatively. These published literatures show that data fusion for remote sensing as an active research field has attractive interests. This paper will review the current situation for pixel-level image fusion technology.

Typically, the algorithms for remote sensing image pixel level fusion can be divided into three general categories shown in Fig. 1 (Yang, et al, 2009): component substitution (CS) fusion technique (Pellemans et al, 1993; Shettigara, 1992; Chavez, 1991; Aiazzi, 2007), modulation-based fusion technique (Liu, 2000; Zhang, 1999; Gangkofner, et al., 2008) and multi-resolution analysis (MRA) based fusion technique (Aiazzi, 2002; Amolins, et al., 2007). In addition, some fusion techniques integrating component substitution with multi-resolution analysis were developed, such as the algorithms combing wavelet transform and IHS transform or PCA transform. Recently, some authors introduce sensors' spectral response and ground spectral features into fusion technology on the basis of previous three categories, and other authors utilize the regularization method to optimize the last fusion results so as to satisfy the higher resolution multispectral image model.

2. COMPONENT SUBSTITUTION FUSION TECHNIQUE

In general, the Component Substitution fusion Technique consists of three steps: Step 1, Forward transform is applied to the multispectral bands after they have been registered to the panchromatic band; Step 2, A component of the new data space similar to the panchromatic band is replaced with the higher resolution band; Step 3, The fused results are finally obtained via inverse transform to the original space.

The typical algorithms of component substitution fusion technique are IHS transform fusion algorithm (Carper, 1990, Shettigara, 1992, Chavez,1991). This algorithm is suitable when exactly three multispectral (MS) bands are concerned since the IHS transform is defined for three components only. Usually, Panchromatic band (PAN) is histogram-matched, i.e., radiometrically transformed by a constant gain and bias in such a way that it exhibits mean and variance that are the same as Intensity, before substitution is carried out. When more than three bands are available, Tu et al (Tu, et al, 2004) present a generalized IHS (GIHS) transform by including the response of the near-infrared (NIR) band into the intensity component. The GIHS-GA (Garzelli and Nencini, 2006) is based on CS strategy and genetic algorithm. The weights of the MS bands in synthesizing the intensity component and the injection gains are achieved by minimizing a global distortion metrics (Q4, in this case) by means of a GA. The GIHS-TP (Choi, 2006) is a CS-based method that trades off the performances of GIHS in terms of spectral distortion and spatial enhancement. Aiazzi et al (Aiazzi, et al, 2007) introduce multivariate regression to improve spectral quality. In the method based on IHS, a generalized intensity component is defined as the weighted average of the MS bands. The weights are obtained as regression coefficients between the MS bands and the spatially degraded PAN image with the aim of capturing the spectral responses of the sensors. Gonzáles Audícana and Otazu (Gonzáles Audícana and Otazu, et al, 2006) present a low computational-cost method to fuse IKONOS images using the spectral response function of its sensors. Andreja and Krisˇtof (Andreja and O. Krisˇtof, 2006) found that for preserving spectral characteristics, high level of similarity between the panchromatic image and the respective multispectral intensity is needed. In order to preserve spectral and spatial resolution, spectral sensitivity of multispectral and panchromatic data was performed, and digital values in individual bands have been modified before fusion. Malpica (Malpica, 2007) present a technique which consists of a hue spectral adjustment scheme integrated with an intensity–hue–saturation transformation for vegetation enhancement. Ling and Ehlers, et al (Ling, Ehlers, et al, 2007) present a method which combines a standard IHS transform with FFT filtering of both the panchromatic image and the intensity component of the original multispectral image.

Other common used CS-based method, PCA transform, (Shettigara, 1992, Chavez,1991) make an assumption that the first principal component (PC) of high variance is an ideal choice for replacing or injecting it with high spatial details from the highresolution histogram-matched PAN image. Shah, et al (Shah, Younan, and King, 2008) use the adaptive PCA to reduce the spectral distortion in the fusion scheme combining adaptive PCA approach and contourlets. Another CS technique reported in the literature is Gram–Schmidt (GS) spectral sharpening (Laben and Brower, 2000), which is widely used since it has been implemented in the Environment for Visualizing Images (ENVI) program package. Aiazzi et al (Aiazzi, et al, 2007) adopts multivariate regression to create the synthetic low-resolution-intensity images which is used in the Gram-Schmidt transform. The proposed enhanced strategy is effective in improving the quality of the images than ordinary GS technique. UNB-pansharp (Zhang, 2002) algorithm developed at the UNB, Canada, is based on CS. The least squares technique is utilized to reduce color distortion, by identifying the best fit between gray values of individual image bands and adjusting the contribution of the individual bands to the fusion result.

3. MODULATION-BASED FUSION

TECHNIQUE

The modulation-based fusion technique utilizes the concept that the spatial details are modulated into the multispectral images by multiplying the multispectral images by the ratio of the panchromatic image to the synthetic image, which is a lower resolution version of the panchromatic image generally. The fusion results are expressed as (1).

$$xs^{H}_{(k,i,j)} = \frac{pan_{(i,j)}}{syn_{(i,j)}} xs^{L}_{(k,i,j)} \qquad (1)$$

$syn_{(i,j)}$ is the value of the (i,j) pixel of the synthetic band. According to the method calculating the synthetic image, the typical modulation based fusion algorithms include:

1) Brovey: $syn_{(i,j)} = \frac{1}{3}\left(R_{(i,j)} + B_{(i,j)} + G_{(i,j)}\right)$ (2);

2) SFIM: $syn_{(i,j)} = \frac{1}{n}\sum_{1}^{n} pan_{(i,j)}$ (3)

, n is the number of k × k neighbors;

3) HPF: $syn_{(i,j)} = LPH(pan)_{(i,j)}$ (4)

, LPH: low-pass filter;

4) SVR: $syn_{(i,j)} = \sum \varphi_k xs^{L}_{(k,i,j)}$ (5)

, $pan = \sum \varphi_k xs^{L}_{(k,i,j)} + \varepsilon$ (6)

, linear regression.

For Brovey transform fusion algorithm (Vrabel, 2000), the synthetic image is the average band of Blue, Green, Red bands, which can be expressed as (2). For Smoothing Filter Based Intensity Modulation (SFIM) fusion algorithm, Liu (Liu, 2000) point out that by using a ratio between a higher resolution image and its low pass filtered (with a smoothing filter) image, spatial details can be modulated to a co-registered lower resolution multispectral image without altering its spectral properties and contrast. The technique can be applied to improve spatial resolution for either colour composites or individual bands. The synthetic image is the local mean of the panchromatic image pixels with 3 x 3, 5 x 5, or 7 x 7 size smoothing filter kernel, which can be expressed as (3). For high-pass filter (HPF) method (Chavez, 1991) the higher spatial resolution data have a small high-pass spatial filter applied. The results of the small high-pass filter contain the high-frequency component that is related mostly to spatial information. The HPF results are added, pixel by pixel, to the lower spatial resolution, but higher spectral resolution data set. This process can be transformed into the form of (1), whose synthetic image can be expressed as (4). Gangkofner et al (Gangkofner, et al, 2008) optimizes the high pass filter addition technique whose improvements are the standardization of the HPF parameters over a wide range of image resolution ratios and the controlled trade-off between resulting image sharpness and spectral properties. Zhang (Zhang, 1999) presents Synthetic Variable Ratio (SVR) merging method which is calculated through the equation (1). The synthetic image is the grey value of the high-resolution synthetic panchromatic image formulated by (5). Zhang had developed a new method that can directly derive parameters φ_i through (6). These parameters φ_i are calculated directly through multiple regression analysis of the original panchromatic image and the original multispectral bands.

4. MULTI-RESOLUTION ANALYSIS FUSION TECHNIQUE

MRA-based fusion techniques (Amolins, et al. 2007) adopt multi-scale decomposition methods such as multi-scale wavelet (Núñez et al. 1999) and Laplacian pyramid (Aiazzi 2002) to decompose multi-spectral and panchromatic images with different levels, and then derive spatial details that are imported into finer scales of the multi-spectral images in the light of the relationship between the panchromatic and multi-spectral images in coarser scales, resulting in enhancement of spatial details. MRA-based fusion techniques consist of three main steps: 1) MRA: Wavelet multi-resolution decomposition; 2) Fusion: Replacement of approximation coefficients of PAN by those of multispectral band; and 3) IMRA: Inverse multi-resolution transform.

It has been found that the earlier studies (Garguet-Duport et al., 1996; Yocky, 1996) adopting discrete wavelet transform (DWT) more preserves the spectral characteristics of the MS imagery than CS fusion schemes (e.g. IHS, PCA), but there are some negative aspects, such as the introduction of artifacts in the fused image. Núñez, et al (Núñez, et al, 1999) present the additive wavelet fusion algorithm (AWL) by using the "`a trous" algorithm which allows to use a dyadic wavelet to merge nondyadic data in a simple and efficient scheme. To improve the spectral quality, the high-pass details are injected proportionally to the low-pass MS components in such a way that the fused MS pixel vector is always proportional to that before fusion. Aiazzi et al present the GLP-CBD fusion algorithm (Aiazzi, et al 2002), which exploits MRA, achieved through GLP, with the spatial frequency response of the analysis filters matching a model of the modulation transfer function (MTF) of the MS instrument. The injection model employs a decision based on locally thresholding the correlation coefficient (CC) between the resampled MS band and the low pass approximation of the Pan. Ranchin et al. (Ranchin et al, 2003) present the “Amélioration de la Résolution Spatiale par Injection de Structures” (ARSIS, Improving Spatial Resolution by Structure Injection) concept based on the assumption that the missing information is linked to the high frequencies of the datasets to be fused. Some fusion techniques jointly using component substitution with multi-scale analysis were developed, such as the algorithms combing wavelet transform and IHS transform (González-Audícana, et al, 2004, Chibani and Houacine, 2002, Zhang and Hong, 2005) or PCA transform (González-Audícana, et al, 2004, Shah, Younan, and King, 2008). These hybrid schemes use wavelets to extract the detail information from one image and standard image transformations to inject it into another image, or propose improvements in the method of injecting information (e.g. Garzelli and Nencini, 2005; Otazu et al., 2005). Otazu et al introduce sensors’ spectral response and ground spectral features into fusion technology on the basis of MRA (Otazu, et al, 2005).

Other authors utilize the regularization method to optimize the fusion results so as to satisfy the higher resolution multispectral image model (Aanæs, et al. 2008). Yang, et al. (2009) generalized this idea and proposed a new model quantifying the mathematical relationship between the fused higher multispectral images and the original multispectral image, the spatial details being extracted from the high-resolution panchromatic image, and the adopted fusion strategies.

5. DISCUSSIONS AND CONCLUSIONS

Currently, the pixel-level image fusion algorithms are divided into three categories, i.e., CS technique, modulation based technique and MRA based technique according to fusion mechanism. With these three categories, similarity and difference between fusion techniques can be derived, which is important for applications. We discuss two typical classes of fusion application, i.e., automatic classification and visual interpretation. Automatic classification relies on the spectral feature than spatial details, while visual interpretation is opposite. Thus, if the fused images are used for automatic classification, modulation based technique and MRA technique with a lower number of decomposition levels are preferable, which better preserve the spectral characteristics of multispectral bands. For visual interpretation, which benefits from spatial and textural details, CS technique and MRA technique with a higher number of decomposition levels are appropriate.

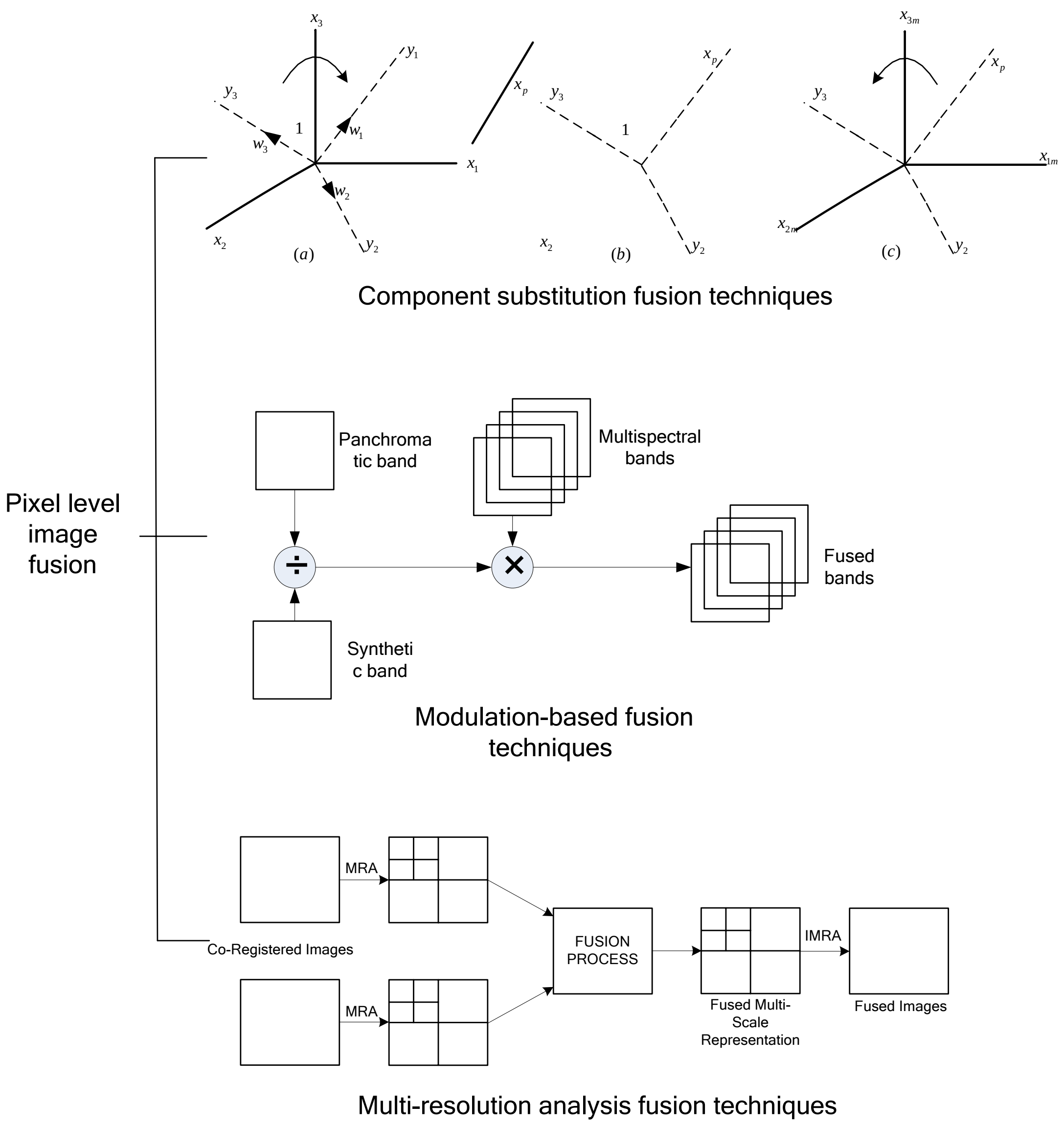

Fig. 1 Three categories of pixel level image fusion

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