GENERALIZED MODEL FOR REMOTELY SENSED DATA PIXEL-LEVEL FUSION

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ABSTRACT:

A generalized model characterizing most remotely sensed data pixel-level fusion techniques is very important for theoretical analysis and applications. This paper focuses on the establishment of a generalized model for most data fusion methods, which is helpful to quantitatively analyze and quickly implement different data fusion techniques. As an example, the PCA fusion method is selected to demonstrate the availability of the generalized model through the generalized model based implementation.

1. NOMENCLATURE

xs_k : the k[th] band of the lower resolution multispectral image;

pan: the higher resolution panchromatic band;

pan^L : the degraded panchromatic band;

pan_A^n : approximation coefficients after n level GLP (Generalized Laplacian Pyramid) or a trous wavelet decomposition;

pan_D^n: detail coefficients after n level GLP or a trous wavelet decomposition;

xs_k^L : the k[th] band of multispectral image resampled or relatively processed to have same size as the panchromatic band;

xs_k^H : the k[th] band of the higher resolution multispectral image after fusion;

$xs_{(k,i,j)}^L$: the pixel value of location (i,j) of the band xs_k^L ;

$xs_{(k,i,j)}^H$: the pixel value of location (i,j) of the band xs_k^H ;

$\delta_{(i,j)}$: spatial and textural details of location (i,j) extracted from the panchromatic band;

$\alpha_{(k,i,j)}$: the fusion coefficients modulating $\delta_{(i,j)}$ into $xs_{(k,i,j)}^L$.

2. INTRODUCTION

So far, many pixel-level fusion methods (Carper,1990, Shettigara,1992, Hill, 1999, Liu,2000, Zhou,1998, Ranchin,2003) for remote sensing image have been presensed where the multispectral image's spatial details are enhanced by adopting the higher resolution panchromatic image corresponding to the lower resolution multispectral image. Therefore, the main principle of remote sensing data fusion focuses on the maximum enhancement of its spatial details on the condition of minimizing distortion of multispectral image's spectral characteristics. When correlation between the multispectral and panchromatic images is not high, it is often a mutual contradiction between maintenance of spectral characteristics and enhancement of spatial details. Thus the choice of fusion algorithm is determined to emphasize spectral features or spatial details according to a specific application. Typical algorithms of remote sensing data fusion can be divided into three general categories (Zhang and Yang,2006): component substitution fusion technique (Chavez,1991, Carper,1990, Shettigara,1992, Hill,1999), modulation-based fusion technique (Chavez,1991, Vrabel, 2000, Liu, 2000, Zhang and Yang,2006) and multi-scale analysis based fusion technique (Zhou,1998, Ranchin,2003, N´u˜nez,1999, Pradhan,2006, Aiazzi,2002). The typical algorithms of component substitution fusion technique are IHS transform fusion algorithm (Carper, 1990), PCA transform fusion algorithm (Shettigara,1992), LCM (Local Correlation Modeling) fusion algorithm (Hill,1999) and RVS (Regression Variable Substitute) fusion algorithm (Shettigara,1992); the fusion algorithms of the modulation-based technique include Brovey transform fusion algorithm (Vrabel,2000), SFIM (Smoothing Filter Based Intensity Moulation) fusion algorithm (Liu,2000) and high pass filter fusion algorithm (Chavez,1991); the fusion algorithms based on the multi-scale analysis mainly include wavelet decomposition based fusion technique (Zhou,1998, Ranchin,2003, N´u˜nez, 1999, Pradhan,2006) and Laplacian pyramid decomposition based fusion technique (Aiazzi,2002).
When various fusion algorithms are studied, an issuse whether these algorithms can be described by a generalized mathematical model (Tu,2001, Wang,2005) is ignored. The model can reflect the main features of the fusion process by a simple mathematical formula. The establishment of a generalized model will contribute to relatively theoretical analysis and fusion algorithm design in the light of a specific application. Also the model is beneficial to qualitative and quantitative analysis of fusion technology from different aspects. The most important aspect is that the establishment of a generalized model will reveal that different fusion technique

rely on the difference of the calculational mehtod of the mathematical model parameters. Thus calulating model parameters corresponding to the fusion method is the main task when implementating the method. Compared to Wang's work (Wang,2005), the paper mainly concentrates on two aspects. First, the paper presents a generalized model for remotely sensed data pixel-level fusion, which has a wide range of applicability. The various commonly used remote sensing data fusion algorithms can be deduced to the generalized model. Second, the implementation technique base on the generalized model only calculates the model parameters impacting the last fusion results and discards the processing steps not affecting the fusion results, saving computational time.

3. THE GENERALIZED MODEL

According to the imaging mechanism and the ideal pan-sharpening results of multispectral image, the presented generalized model is formulated by,

$$xs^H_{(k,i,j)} = xs^L_{(k,i,j)} + \alpha_{(k,i,j)} \cdot \delta_{(i,j)} \tag{1}$$

$\delta_{(i,j)}$: Spatial and textural details extracted from the panchromatic band by a certain calculation.

$\alpha_{(k,i,j)}$: The coefficients modulating $\delta_{(i,j)}$ into $xs^L_{(k,i,j)}$.

The presented model expressed by equation (1) can clearly describe the mathematical relationships among the original multispectral image, the spatial details extracted from the high-resolution panchromatic image, and the adopted fusion strategy. In another word, the spatial and textural features extracted from the panchromatic band are imported into the multispectral image in terms of the fusion coefficients and the fusion result is the image whose features are enhanced by the panchromatic image. The fusion operations are fulfiled pixel by pixel, band by band after calculation of $\delta_{(i,j)}$ and $\alpha_{(k,i,j)}$, but in the course of calculation of $\delta_{(i,j)}$ and $\alpha_{(k,i,j)}$, not only the pixel value of location (i,j) of the lower resolution multispectral k^{th} band and the panchromatic band but also the whole statistical information and neighbor pixels of loacation (i,j) are used.

the methods calculating parameters $\delta_{(i,j)}$ include:

1) the linear combination method: obtaining the $\delta_{(x,y)}$ after subtracting multispectral bands' linear combination from the panchromatic band, such as IHS, PCA, RVS, Brovey, Block-regression (Zhang and Yang,2006);

2) filter method and multi-scale analysis method: obtaining the $\delta_{(x,y)}$ after subtracting its filtered or multi-level decomposition results from the panchromatic band, such as SFIM, LCM，A trous (N´u˜nez,1999), GLP (Aiazzi,2002), ARSIS method (Ranchin,2003).

$\alpha_{(k,x,y)}$ is determined by following factors: the panchromatic and multispectral relative spectral response, spectral range of the panchromatic and multispectral bands, the GIFOV(Ground projected Instantaneous Field Of View) of panchromatic and multispectral bands, the landscape properties and land cover classes, radiometric calibration method of different sensors, the temporal properties, the correlation between the panchromatic and multispectral bands, the average value，variance and other statictical characteristics of the multispectral and panchromatic bands.

The methods calculating parameters $\alpha_{(k,x,y)}$ include:

1) Constant Value, such as IHS，PCA, RVS, A trous, LCM;

2) Spectral Distortion Minimum: such as SFIM，Brovey, A trous, Block-regression;

3） Context-based Decision (CBD)，such as GLP，ARSIS.

The model formulated by equation (1) is more comprehensive and applicable than Wang's model. The fusion coefficients of wang's model are limited to the cases of constant value and spectral distortion minimum, and can not describe the fusion coefficients for LCM, ARSIS and GLP fusion algorithms. For the method extracting spatial and textural details, Wang's model include the filter and linear combination mehtods while the generalized mode proposed in this paper supports the additional methods used in LCM and GLP fusion algorithms. In a word, the generalized model can characterize most of commonly used remote sensing data fusion algorithms including not only the IHS，PCA，A trous，Brovey，HPF algorithms but also RVS, GLP, LCM, ARSIS, wavelet decomposition plus PCA transform, wavelet decomposition plus IHS transform, and the authors proposed Block-regression.

4. DEDUCTION FOR COMMONLY USED FUSION ALGORITHMS

In this section, three categories of fusion algorithms mentioned in section 1 are deduced to the generalized model, i.e. the proposed equation (1), through the mathematical transformation. Through the deduction, the conclusion can be drawn that different fusion technique rely on the difference of the calculation of parameters $\delta_{(i,j)}$ and $\alpha_{(k,i,j)}$.

4.1 Component Substitution Fusion Technique

The typical algorithms applying component substitution fusion technique include IHS, PCA, LCM and RVS fusion algorithms. To illustrate the deduction for this technique, following is the transformation steps taking PCA fusion algorithm as an example.

The lower resolution multispectral band xs_k is resampled to have the same size as the higher resolution panchromatic band pan after those bands are co-registrated: $xs^L_k = rsp(xs_k)$, and after the resampling the implementatiom steps for PCA fusion algorithm are as follows (Shettigara,1992):

1) Calculating the correlation matrix of the n lower resolution multispectral bands, n is equal to 4;

2) Calculating the eigenvalues and eigenvectors according to the correlation matrix;

3) Sorting the eigenvalues and eigenvectors;

4) Calculating the principal components one by one according the PCA transform;

$$pc = \Phi \cdot xs^L \tag{2}$$

5) Selecting the first principal component;

6) Replacing the first principal component by the higher resolution band;

$$pan_{(i,j)} = pc_{(1,i,j)} + \delta_{(i,j)} \tag{3}$$

7) Obtaining the fusion results after inverse PCA transform

$$xs^H = \Omega \cdot pc' \text{, where } \Omega = \Phi^{-1} \tag{4}$$

$$\begin{aligned}
\begin{bmatrix} xs_1^H \\ xs_2^H \\ xs_3^H \\ xs_4^H \end{bmatrix} &= \begin{bmatrix} \omega_{11} & \omega_{12} & \omega_{13} & \omega_{14} \\ \omega_{21} & \omega_{22} & \omega_{23} & \omega_{24} \\ \omega_{31} & \omega_{32} & \omega_{33} & \omega_{34} \\ \omega_{41} & \omega_{42} & \omega_{43} & \omega_{44} \end{bmatrix} \cdot \begin{bmatrix} pan \\ pc_2 \\ pc_3 \\ pc_4 \end{bmatrix} = \begin{bmatrix} \omega_{11} & \omega_{12} & \omega_{13} & \omega_{14} \\ \omega_{21} & \omega_{22} & \omega_{23} & \omega_{24} \\ \omega_{31} & \omega_{32} & \omega_{33} & \omega_{34} \\ \omega_{41} & \omega_{42} & \omega_{43} & \omega_{44} \end{bmatrix} \cdot \begin{bmatrix} pc_1 + \delta \\ pc_2 \\ pc_3 \\ pc_4 \end{bmatrix} \\
&= \begin{bmatrix} \omega_{11} \\ \omega_{21} \\ \omega_{31} \\ \omega_{41} \end{bmatrix} \cdot (pc_1 + \delta) + \begin{bmatrix} \omega_{12} & \omega_{13} & \omega_{14} \\ \omega_{22} & \omega_{23} & \omega_{24} \\ \omega_{32} & \omega_{33} & \omega_{34} \\ \omega_{42} & \omega_{43} & \omega_{44} \end{bmatrix} \cdot \begin{bmatrix} pc_2 \\ pc_3 \\ pc_4 \end{bmatrix} = \begin{bmatrix} \omega_{11} \\ \omega_{21} \\ \omega_{31} \\ \omega_{41} \end{bmatrix} \cdot pc_1 + \begin{bmatrix} \omega_{12} & \omega_{13} & \omega_{14} \\ \omega_{22} & \omega_{23} & \omega_{24} \\ \omega_{32} & \omega_{33} & \omega_{34} \\ \omega_{42} & \omega_{43} & \omega_{44} \end{bmatrix} \cdot \begin{bmatrix} pc_2 \\ pc_3 \\ pc_4 \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{21} \\ \omega_{31} \\ \omega_{41} \end{bmatrix} \cdot \delta \\
&= \begin{bmatrix} \omega_{11} & \omega_{12} & \omega_{13} & \omega_{14} \\ \omega_{21} & \omega_{22} & \omega_{23} & \omega_{24} \\ \omega_{31} & \omega_{32} & \omega_{33} & \omega_{34} \\ \omega_{41} & \omega_{42} & \omega_{43} & \omega_{44} \end{bmatrix} \cdot \begin{bmatrix} pc_1 \\ pc_2 \\ pc_3 \\ pc_4 \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{21} \\ \omega_{31} \\ \omega_{41} \end{bmatrix} \cdot \delta = \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{21} \\ \omega_{31} \\ \omega_{41} \end{bmatrix} \cdot \delta
\end{aligned} \tag{5}$$

Thus, the whole algorithm mainly consists of calculating the correlation matrix, forward PCA transform and inverse PCA transform. Through deduction the final fusion results are

$$xs^H_{(k,i,j)} = xs^L_{(k,i,j)} + \omega_{k1} \cdot \delta_{(i,j)} \text{, where } \delta = pan - pc_1 \tag{6}$$

4.2 Modulation-based Fusion Technique

The typical algorithms applying the modulation-based fusion technique include Brovey, SFIM and HPF fusion algorithms. To illustrate the deduction for the modulation-based fusion technique, following is the transformation steps taking Block-regression fusion algorithm presented by the authors as an example.

The lower resolution multispectral band xs_k is resampled to have the same size as the higher resolution panchromatic band pan after those bands are co-registrated: $xs_k^L = rsp(xs_k)$, and after the resampling the implementatiom steps for Block-regression based fusion algorithm are as follows (Zhang and Yang,2006):

1) Obtaining linear regression coefficients through multiple linear regression between the blocks from the panchromatic band and from the multispectral bands. n is equal to 4;

$$pan = c_1 \cdot xs_1^L + c_2 \cdot xs_2^L + c_3 \cdot xs_3^L + c_4 \cdot xs_4^L + \delta \tag{7}$$

2) Computing the linear combination of blocks from multispectral bands in terms of coefficients.

$$syn = c_1 \cdot xs_1^L + c_2 \cdot xs_2^L + c_3 \cdot xs_3^L + c_4 \cdot xs_4^L \tag{8}$$

3) Finishing the fusion operation for every block using the following expression:

$$\begin{aligned}
\begin{bmatrix} xs_1^H \\ xs_2^H \\ xs_3^H \\ xs_4^H \end{bmatrix} &= \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} \cdot \frac{pan}{syn} = \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} \cdot \frac{syn + \delta}{syn} = \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} \cdot \left(1 + \frac{\delta}{syn}\right) \\
&= \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} + \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} \cdot \frac{\delta}{syn} = \begin{bmatrix} xs_1^L \\ xs_2^L \\ xs_3^L \\ xs_4^L \end{bmatrix} + \begin{bmatrix} xs_1^L / syn \\ xs_2^L / syn \\ xs_3^L / syn \\ xs_4^L / syn \end{bmatrix} \cdot \delta
\end{aligned} \tag{9}$$

Thus, the Block-regression based fusion algorithm can be modeled by the following simple formula:

$$xs^H_{(k,i,j)} = xs^L_{(k,i,j)} + \frac{xs^L_{(k,i,j)}}{\sum_k c_k \cdot xs^L_{(k,i,j)}} \cdot \delta_{(i,j)} \tag{10}$$

Where $\delta = pan - (c_1 \cdot xs_1^L + c_2 \cdot xs_2^L + c_3 \cdot xs_3^L + c_4 \cdot xs_4^L)$, c_k is the regression coefficients of the block including pixel (i,j) .

4.3 Multi-scale Analysis based Fusion Technique

Multi-scale analysis based fusion technique adopts multi-scale decomposition methods such as multi-scale wavelet (Zhou,1998, Ranchin,2003, N´u˜nez,1999, Pradhan,2006), Laplacian pyramid (Aiazzi,2002) to decomposize multispectral and panchromatic images with different levels, and then derives spatial details which are imported into finer scales of the multispectral images in the light of the relationship between the panchromatic and multispectral images in coarser scales (Ranchin,2003, Aiazzi,2002, Garzelli,2005), resulting in enhancement of spatial details.

The typical fusion algorithms based on multi-scale analysis include a trous fusion algorithm which adopts translation invariant and undecimated wavelet transform and Laplacian pyramid decomposition based fusion algorithm. Some fusion methods combining component substitution and wavelet decomposition are recently presented, such as methods combining wavelet decomposition and PCA transform or IHS transform. To illustrate the deduction for the multi-scale analysis based fusion technique, following is the transformation steps taking ARSIS as an example.

The lower resolution multispectral band xs_k is resampled to have the same size as the higher resolution panchromatic band pan after those bands are co-registrated: $xs_k^L = rsp(xs_k)$, and after the resampling the implementatiom steps for ARSIS fusion algorithm are as follows (Ranchin,2003):

1) Obtaining pan_A^n, which is approximation coefficients after n level GLP or a trous, or UDWT(Undecimated Discrete Wavelet Transform) decomposition of the panchromatic band pan $\delta = pan - pan_A^n = \sum_n pan_D^n$.

2) Finishing the fusion operation for every pixel using the following expression:

$$xs^H_{(k,i,j)} = xs^L_{(k,i,j)} + \alpha_{(k,i,j)} \cdot \delta_{(i,j)} \tag{11}$$

Context-based decision (CBD) model (Ranchin,2003):

$$\alpha_{(k,i,j)} = \begin{cases} \min\left(\dfrac{\sigma^{xs}_{(k,i,j)}}{1+\sigma^{pan}_{(i,j)}}, 3\right), & \text{if } \rho_{(k,i,j)} \geq \theta_k \\ 0, & \text{if } \rho_{(k,i,j)} < \theta_k \end{cases} \tag{12}$$

where：

1) $\rho_{(k,i,j)}$ is the correlation coefficient between the $xs^L_{(k,i,j)}$'s N x N neibors （9x9 for IKONOS，7x7 for SPOT 1-4） and $pan^n_{A(i,j)}$'s relative pixel window.

2) θ_k is the threshold value for the k[th] band, ranging from 0.3 ~ 0.6, which depends on whole correlation between the multispectral band and the panchromatic band. The smaller the correlation, the bigger the threshold value is.

3) $\sigma^{xs}_{(k,i,j)}$ is standard deviation of the $xs^L_{(k,i,j)}$'s N x N neibors, and $\sigma^{pan}_{(i,j)}$ is standard deviation of the $pan^n_{A(i,j)}$'s N x N neibors.

$\alpha_{(k,i,j)}$ is also determinded by Ranchin-Wald-Mangolini (RWM) (Ranchin, 2003).

5. PCA FUSION IMPLEMENTATION METHOD BASED ON THE GENERALIZED MODEL

To demonstrate availability of the generalized model, the generalized model based implementation and experiments are given as well as comparison with the regular implementation taking PCA fusion technique as an example.

The regular PCA fusion implementation mainly consists of three steps. Firstly, the multispectral bands data is forward transformed into a new data space; secondly, the principle component of new data space is substituted by the higher resolution band, i.e., the panchromatic band; lastly, the data space after replacement is inversely transformed into the original space. In general, the regular implementation operations include calculation of transformation matrix, forward transformation and inverse transformation.

Through the above mathmatical transformation in the section 4.1, the PCA fusion technique can be deduced to the form of equation (13). Thus, the generalized model based implementation for this fusion technique can be fulfilled by equation (13) pixel by pixel.

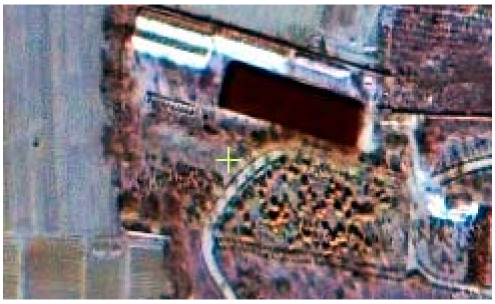
$$xs^H_{(k,i,j)} = xs^L_{(k,i,j)} + \omega_{k1} \cdot \delta_{(i,j)} \tag{13}$$

$$\delta = pan - pc_1 \tag{14}$$

$$pc_1 = \varphi_{11} \cdot xs_1^L + \varphi_{12} \cdot xs_2^L + \varphi_{13} \cdot xs_3^L + \varphi_{14} \cdot xs_4^L \tag{15}$$

The parameters φ_{k1} and ω_{k1} are elements of forward and inverse transform matrix, respectively. Compared to the regular implementation, the new implementation does not require the forward and inverse transformation and just concentrates on the calculation of ω_{k1} and $\delta_{(i,j)}$, decreasing computational requirements.

(a) Original multispectral, true color composite 441 x 413 (b) PCA fusion results, 1761 x 1649



(c) a slice of regular implementation (d) a slice of generalized model based implementation

Fig.1 Fusion results of the regular implementation and the generalized model based implementation

The experimental data consists of a slice of IKONOS panchromatic band with 1761 x 1649 pixels, and the cooresponding multispectral image with 441 x 413 pixels including B, G, R, NIR bands. We write Matlab programs to perform the fusion operations using the regular method and generalized model based method, respectively, in the same hardware and software platform. The experimental results show that the runtime not including resampling time of the multispectral image, input and output time for the new implementation is 1.0938s, while the time for the regular implementation is 1.3906s, saving 0.2969s or 21.35%. At the same time, the pixel value of the two types of fusion results, shown in fig.1 (c) for regular implementation and fig.1 (d) for the generalized model based implementation, is the same. Fig.1 (a) and fig.1 (b) are the original multispectral image and PCA fusion results, respectively.

6. CONCLUSIONS

This paper presents the generalized model for remotely sensed data pixel-level fusion, which can clearly describe the relationships among the original multispectral image, the spatial details extracted from the high-resolution panchromatic image, and the adopted fusion strategy by means of mathematical expression. The generalized model can characterize most commonly used remote sensing data fusion algorithms and these algorithms can be deduced to the generalized model through mathematical transformation. Therefore, the establishment of the generalized model will contribute to design of fusion algorithms whose principal contradictions concentrate on the methods extracting spatial details from high-resolution panchromatic images and the strategies adding the spatial details to multispectral images. At the same time, the proposed remotely sensed data fusion algorithms can been theoretically analysized and translated into the framework of the generalized model after estabishing the model. It proves that the implementation technique based on the generalized model have the advantages reducing the computational requirements and having universal applicabilities by means of the experimental comparison and mathematical transformation.The implementation technique can be applied to most of remote sensing data fusion algorithms, in particular for the data fusion algorithms demanding huge calculations, the decreased operations is large.

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