Fuzzy Weighted Least Square Filter for Pansharpening in Satellite Images

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Abstract: Many remote sensing applications require images with both high spatial and spectral resolution. But due to the technological limitations of satellite sensors, the spatial and spectral details will not present in a single image. Pan-sharpening combines a low spatial resolution multispectral image with a high spatial resolution panchromatic image to create a fused color image with both spatial and spectral resolution. There are a number of applications in remote sensing that require images with both high spatial and spectral resolutions

Keywords: Remote sensing, satellite image, Pan-sharpening, Fuzzy weighted least square filter, high resolution image.

1. Introduction

The remote sensing satellite sensors have several limitations such as less space for data storage, minimum bandwidth for communication with earth station etc. So,the remote sensing satellites cannot capture the high spatial and spectral resolution images simultaneously. Generally, the satellite sensors capture the remote sensing images as two types of images such as a panchromatic image and a multispectral image. The panchromatic image gives clear information about the spatial resolution while, the color (spectral) information will be missing. In converse, the multispectral image provides clear information about the color, but the spatial information will be missing [1].Pan sharpening is atechniqueforfusing the panchromatic image and multispectral images, which combines the high resolution panchromatic image and low resolution multispectral image to generate an image with both high spatial and spectral resolution.

In this paper, pansharpening with the aid of Fuzzy weighted least square filter, which eliminates the low frequency components of the pan and MS images is proposed. The organization of the paper is as follows: Section 2 briefly describes some of the existing filtering based pansharpening techniques. The proposed work is described in section 3. Section 4 provides the results and discussion section and the conclusion is provided in section 5.

2. Literature Survey

Among the various pan sharpening techniques, the most commonly used techniques are intensity-hue-saturation (IHS) method [2], Principal Component Analysis (PCA) [3] and Brovey Transform (BT) [4]. These methods can maintain the spatial resolution same as the panchromatic image but the spectral characteristics of the multispectral image will be distorted. Wavelet transform based technique preserves the spectral information of the image but it does not preserve the spatial information[5].

Pan sharpening methods based on filters are also common, in which the spatial information is extracted from the panchromatic image and it is injected into the multispectral image. In High Pass Filtering (HPF)

method [6], high pass filter is used to extract the high frequency components of the panchromatic image and this high frequency component is added to each band of the multispectral image. This method preserves the spectral characteristics of the multispectral image. In [7], Kaplan and Erer proposed a technique in which a multiscale bilateral filter is used to decompose the high spatial resolution pan image and it is used as the high frequency information of the low resolution multispectral image. Pan sharpening based on subband decomposition of pan and multispectral images using 1-D lattice filter structure is proposed in [8]. In this approach, the pansharpened image is obtained by combining the sub band of bothimages using undecimated lattice reconstruction structure and some predefined rules. An adaptive pansharpening technique using weighted least square (WLS) filter is proposed in [9]. This approach uses WLS filter to eradicate the influence of the low-frequency components of the Pan and MS images. The experimental result shows that this approach performs well in preserving both spatial and spectral characteristics.

3. Proposed Work

IHS method is a very basic and simple technique in pan sharpening of satellite images [2]. But this method has several drawbacks such as the presence of low frequency components in the detail map results in spectral distortion and local artifacts may arise because all the bands of the multispectral image share the same detail map. In order to solve these problems, FuzzyWeighted least square filter is proposed in this work, which eliminates the influence of low frequency components. The FWLS filter estimates the low frequency components of the pan and MS images before finding the detail map. Furthermore the estimated detail map is refined with the spectral signatures of the different bands of the MS image. Then the refined detail maps are injected into the corresponding bands of the MS image to obtain the high resolution multispectral image.

The FWLS filter is an edge preserving filter, used to smooth the images without affecting the edges of the image. The edges are preserved by compromising between sharpening and blurring. In this work, the FWLS filter is used as low pass filter to estimate the low frequency components of the pan and MS images.

For an input image I, we require a filtered image I_f, which should be maximally close to I and as smooth as possible everywhere, except the edges. The filtered image I_f can be obtained as follows:

$$\arg\min_{I_f}\left(\left\|I_f - I\right\|^2 + \lambda\left(w_x\left(\frac{\partial I_f}{\partial x}\right)^2 + w_y\left(\frac{\partial I_f}{\partial y}\right)^2\right)\right)$$

where, the first term $\left\|I_f - I\right\|^2$ ensures that the distance between I_f and I is minimum. The second term is for achieving smoothness by minimizing the partial derivative of I_f. w_x and w_y are smoothness weights. λ is the regularization factor for balancing the two terms.

The flowchart of the proposed method is given below (Fig. 1).

Initially, the low frequency component of the MS image $\left(MS_L\right)$ and the pan image $\left(P_L\right)$ is estimated using the FWLS filter. The difference between the original images and the low frequency components are considered as the high frequency components (MS_H and P_H). Based on the high frequency components, the primitive detail map is estimated. The estimated primitive detail map may not be optimal, because different bands of the high resolution multispectral image share the same detail map, which may cause local artifacts. So, the primitive detail map is refined to generate final detail maps for each band. Finally, the primitive detail map is injected into the corresponding bands of the multispectral image to obtain the high resolution multispectral image.
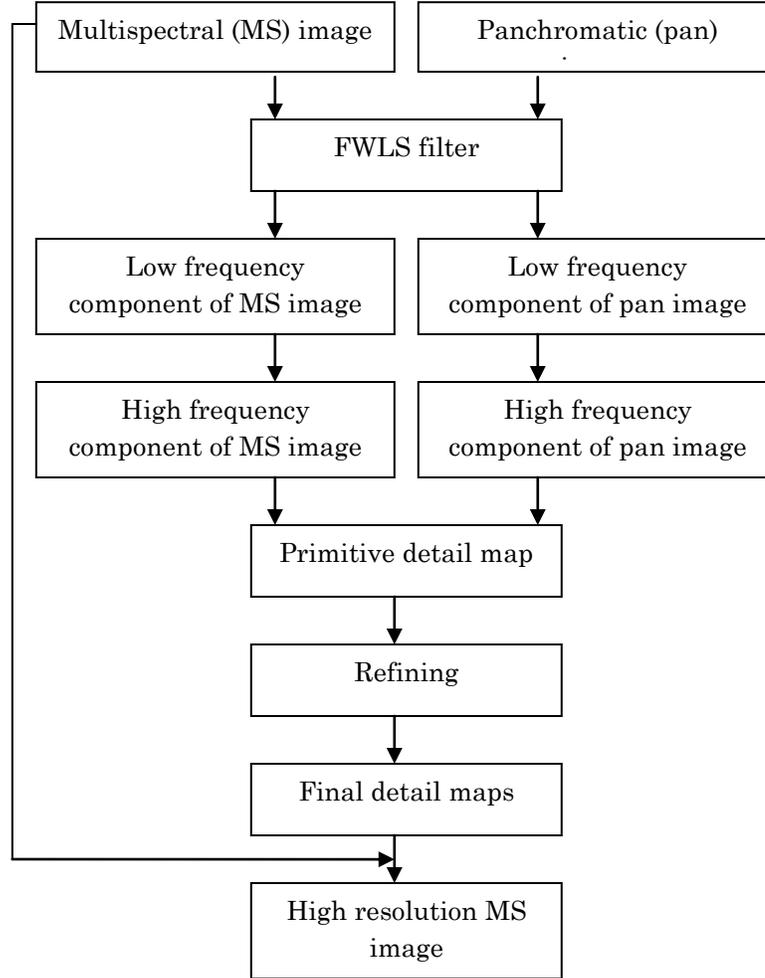
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┌─────────────────────────┐     ┌─────────────────────────┐
│ Multispectral (MS) image│     │   Panchromatic (pan)    │
└─────────────────────────┘     └─────────────────────────┘
              │                             │
              ▼                             ▼
        ┌──────────────────────────────────┐
        │            FWLS filter           │
        └──────────────────────────────────┘
              │                             │
              ▼                             ▼
┌─────────────────────────┐     ┌─────────────────────────┐
│    Low frequency         │     │    Low frequency         │
│ component of MS image    │     │ component of pan image   │
└─────────────────────────┘     └─────────────────────────┘
              │                             │
              ▼                             ▼
┌─────────────────────────┐     ┌─────────────────────────┐
│    High frequency        │     │    High frequency        │
│ component of MS image    │     │ component of pan image   │
└─────────────────────────┘     └─────────────────────────┘
              │                             │
              ▼                             ▼
        ┌──────────────────────────────────┐
        │        Primitive detail map      │
        └──────────────────────────────────┘
                          │
                          ▼
        ┌──────────────────────────────────┐
        │             Refining             │
        └──────────────────────────────────┘
                          │
                          ▼
        ┌──────────────────────────────────┐
        │         Final detail maps        │
        └──────────────────────────────────┘
                          │
                          ▼
        ┌──────────────────────────────────┐
        │        High resolution MS        │
        │             image                │
        └──────────────────────────────────┘
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Figure 1. *Flow chart of the proposed method*

3.1 Estimation of Primitive Detail Map

The decomposition of the pan and MS images into low frequency and high frequency components are expressed as follows.

$$P = P_L \oplus P_H \tag{1}$$

$$MS^i = MS_L^i \oplus MS_H^i \tag{2}$$

where, $\oplus$ refers to an operation which combines the low frequency components and high frequency components into an image. P_L and P_H are the low frequency components and high frequency components of the pan image, respectively. MS^i represents the ith band if the MS image. MS_L^i and MS_H^i are the low frequency components and high frequency components of the MS image, respectively.

In order to eliminate the influence of low frequency components, the primitive detail map D is estimated as follows:

$$D = P_H \quad I_H \tag{3}$$

where, I_H represents the high frequency components of the intensity band I and it is calculated as follows:

$$I_H = \sum_{i=1}^{N} a^i MS_H^i \tag{4}$$

where, a^i is the band coefficient of MS_H^i.

From equ. (3) and (4), it is clear that, to estimate the primitive detail map D, we need to calculate P_H, α^i and MS_H^i.

The low frequency components P_L and MS_L^i are obtained by applying the FWLS filter.

$$P_L = F(P) \tag{5}$$

$$MS_L^i = F\big(MS^i\big) \tag{6}$$

where, $F(\bullet)$ refers to the operator of FWLS filter. By applying inverse operation on equ. (1) and (2), P_H and MS_H^i can be obtained, respectively.

Using I_H, P_H can be approximated as close as possible [10]. Therefore,

$$P_H \approx \sum_{i=1}^{N} \alpha^i MS_H^i \tag{7}$$

Using least square estimation, the optimal coefficient α^i is calculated as follows:

$$\alpha^i = \left[\big(MS_H^i\big)^T MS_H^i \right]^{-1} \big(MS_H^i\big)^T P_H \tag{8}$$

Using α^i, I_H can be obtained as shown in equ. (4), and from equ. (3), the primitive detail map can be obtained.

3.2 Refinement of Primitive Detail Map

In general, after obtaining the detail map, the high resolution multispectral (HMS) image is formed as follow.

$$HMS^i = MS^i + D \tag{9}$$

But, here it is considered that, each band of the MS each has its own detail map. Therefore, the above equation can be rewritten as,

$$HMS^i = MS^i + D^i \tag{10}$$

where, D^i indicated the final detail map of the ith band.

It is assumed that the low frequency component of the MS image are approximately equal to the low frequency components of the HMS image. After neglecting the low frequency component in equ. (10), we have,

$$HMS_H^i = MS_H^i + D^i \tag{11}$$

where, HMS_H^i indicates the high frequency component of the ith band of the HMS image. Similar to equ. (4), high frequency component of the intensity band of HMS image HI_H can be represented as,

$$HI_H = \sum_{i=1}^{N} \alpha^i HMS_H^i = \sum_{i=1}^{N} \alpha^i \big(MS_H^i + D^i \big) \tag{12}$$

For each pixel, if HI_H is closer to P_H, then the spatial quality of the fused high resolution multispectral image will be higher. With respect to the estimated final detail map, the function F is minimized as follows:

$$\arg\min_{D^i} F\big(D^i\big) = \left\| P_H - \sum_{i=1}^{N} \alpha^i \big(MS_H^i + D^i\big) \right\|^2 \tag{13}$$

By refining the primitive detail map D, D^i can be calculated with the steepest descent method. Further updation of D_i can be done as follows:

$$D_{(n+1)}^i = D_{(n)}^i - \gamma \left. \frac{\partial F}{\partial D^i} \right|_{D^i = D_{(n)}^i} \tag{14}$$

where, the initial value $D_{(0)}^i = D$, and γ is the step size and it must be a small positive number. The iterative process will converge to a solution. After finding the final detail map D^i, the high resolution multispectral image can be obtained by using equ. (10).

4. Experimental Results and Analysis

4.1 Experimental Setup

The input pan image, low resolution multispectral image and the output high resolution multispectral image are shown in figure 2.
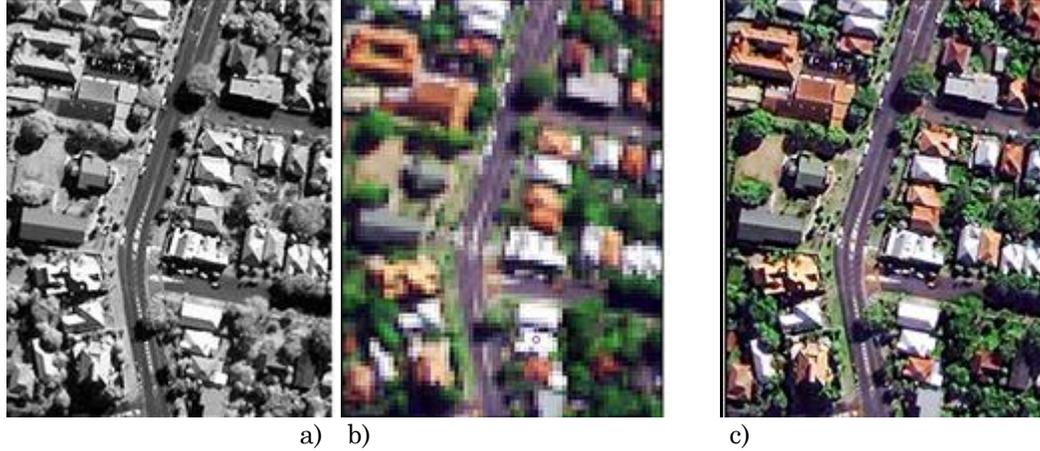

a)   b)   c)

Figure 2. *Input and output images a) pan image b) low resolution MS image*
c) high resolution MS image

The multispectral images of these satellites contain four bands such as R,G,B and NIR. Initially, the original pan images and multispectral images are downsampled to a lower resolution by a downsampling factor of $1/4$. The downsampled multispectral image is sharpened back to its original resolution, and the original multispectral images are regarded as the high resolution multispectral image for reference. The parameters are set as follows: The regularization factor $\lambda = 0.8$ and the step size $\gamma = 0.1$. Sixpansharpening methods such as IHS method [9],AIHS method [11], the À trous wavelet transform-based (AWLP) method [12], the Generalized Laplacian Pyramid (GLP) method [13], the Gram–Schmidt Adaptive (GSA) method [14], and the Bilateral filter-based (BFLP) method [15] are used for the comparing the performance of the proposed method.

Six global metrics are utilized to evaluate the performance of different pansharpening methods.

i) Correlation coefficient (CC)

It measures the correlation between the sharpened result and the reference. The sharpened result is closer to the reference when CC is smaller.

ii) Relative dimensionless global error in synthesis (ERGAS)

It measures the global quality of the sharpened result. The better sharpened result has a smaller value.

iii) Universal image quality indexes (UIQI)

It reflect the loss of correlation, luminance distortion, and contrast distortion. The higher the value of UIQI, the higher the spectral quality. The highest value for UIQI is 1.

iv) Spectral angle mapper (SAM)

It denotes the absolute value of the spectral angle between the sharpened result and the reference vectors. A small SAM value means small spectral angle distortion.

v) Relative average spectral error (RASE)

It characterizes the average performance in the spectral bands. The lower the value of RASE, the higher the spectral quality.

vi) Root-mean-square error (RMSE)

It indicates the average squared difference between the sharpened result andthe reference. The smaller the RMSE, the better the performance is.

4.2 Comparison of Different Pansharpening Methods

The quantitative evaluation of the different pansharpening methods are given in table 1. From the table it is clear that the proposed method outperforms other methods interms of both spatial and spectral quality. For the comparison, it can be noted that the high resolution image obtained by the proposed method is similar to the reference high resolution multispectral image.

Table 1. *Performance evaluation*

	CC	ERGAS	UIQI	SAM	RASE	RMSE
IHS						
AIHS	0.933	6.107	0.932	0.063	23.882	73.494
AWLP	0.946	5.994	0.941	0.059	24.092	74.142
GLP	0.952	5.487	0.950	0.065	21.865	67.287
GSA	0.944	6.207	0.940	0.074	24.100	74.167
BFLP	0.959	4.941	0.957	0.056	20.061	61.735
Proposed						

5. Conclusion

In this paper, a novel pansharpening method using Fuzzy Weighted Least Square filter was proposed. Different from the existing methods, the proposed method used FWLS filter to eliminate the low frequency components of the pan image and multispectral image. The proposed FWLS filter is used to calculate the low frequency components of the pan and MS images before finding the detail map. Furthermore, the spectral signatures of the different bands of the MS image are refined with the detail map. Then, the refined detail maps are injected into the corresponding bands of the MS image so as to generate the high resolution multispectral image. The performance of the proposed method is evaluated using CC, ERGAS, UIQI, SAM, RASE, and RMSE, respectively. On comparing with the existing methods, the proposed method performs well in terms of both spatial and spectral quality.

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