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Journal Of Radar and Optical Remote Sensing

JRORS 1 (2019) 22–30

Using Discrete Wavelet Transform to increase the Accuracy of Hyper Spectral and High Resolution Images Fusion

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Received 18 December 2018; revised 19 May 2019; accepted 24 May 2019

Abstract

In optical remote sensing, hyper-spectral (HS) image which contains color information is produced by hundreds of spectral bands. Because of the trade-off imposed by the physical constraint between spatial and spectral resolutions, the HS image has poor spatial resolution. On the contrary, the panchromatic (PAN) images have high spatial resolution but no color information. Image fusion can combine the geometric detail of PAN image and the color information of the HS image to produce a high-resolution HS image. The aim of this study is the fusion of Hyperion and OrbView-3 PAN images based on Discrete Wavelet Transform (DWT). Firstly, the preprocessing methods were applied on Hyperion and OrbView-3 images and registration method based on nearest neighbor method were applied on two dataset. In order to fit images pixel size, the resampling operation was applied. PAN image was decomposed by DWT and then fused by hyper spectral image with GST algorithm. DIV, CC, Q and RMSE accuracy assessment methods were used on final fused image to evaluate the results accuracy. The results showed that using DWT based decomposition PAN image, preserve the spatial information during fusion rule. Also this technique gains high accuracy in term of spectral information of hyper spectral image.

Keywords: Discrete Wavelet Transform (DWT), Hyperion, OrbView-3, Accuracy assessment

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1. Introduction

In real world applications where various optical sensors are used for image acquisition, it is often difficult to obtain a good quality image by a single sensor (Omar and Stathaki, 2014). Image fusion is an efficient way of retrieving the information from multiple sources into one image (Dogra et al., 2018). Fusion of two images acquired from different sources has many applications (Hasani Moghaddam., 2018): medical (Nandeesh and Meenakshi, 2015; Galande and Patil, 2013), vegetation detection and monitoring (Gasparovic et al., 2018), urban studies (Lino et al., 2018), climate (Kar and Banerjee, 2018), etc. One of the important pre-processing steps for the fusion process is image registration. Image registration is the process of transforming different sets of data into one coordinate system (Rani and Sharma, 2013). Wavelet hypothesis is an expansion of Fourier hypothesis and it is acquainted as an option with the brief span Fourier change (Bopche and Gade, 2018). Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower frequency band, and higher frequency bands (Maddali et al., 2012). In discrete wavelet transform (DWT), a two channel filter band is used. When decomposition is performed, the approximation and detail component can be separated and 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain (Rani and Sharma, 2013).

Li et al., (2018), to reduce the spectral distortions of fused images focusing on optimizing the approach used to extract spatial details from the PAN band, or on the optimization of the models employed during the injection of spatial details into the MS bands. The HR, GSA and SFIM algorithms applied on images; the results showed that the proposed method offers the lowest spectral distortions and more sharpened boundaries between different image objects than other methods, especially for boundaries between vegetation and non-vegetation objects.

Xia et al. (2018), to solve the low frequency sub band coefficients obtained by the NSCT decomposition which is not conducive to maintaining the details of the source image, proposed a medical image fusion algorithm that combined with sparse representation and pulse coupling neural network. In this method, the source image was initially decomposed into low and high frequency sub band coefficients by NSCT transform, Secondly, the K singular value decomposition (K-SVD) method is used to train the low frequency sub and coefficients. The experimental results and analysis showed that the algorithm of gray and color image fusion is about 34% and 10% higher than the contrast algorithm in the edge information transfer factor QAB/F index, and the performance of the fusion result is better than the existing algorithm.

He et al. (2018), to better preserve the interesting region and its corresponding detail information, proposed a novel multi scale fusion scheme based on interesting region detection. In this method first, the Mean Shift is used to detect the interesting region with the salient objects and the background region of IR and VI. Then the interesting regions are processed by the guided filter. The results demonstrated that the proposed algorithm can integrate more background details as well as highlight the interesting region with the salient objects, which is superior to the conventional methods in objective quality evaluations and visual inspection.

Borsoi et al. (2018), introduced a novel Hyper spectral- Multi spectral image fusion strategy that combined an un-mixing-based formulation with an explicit parametric model for typical spectral variability between the two images. Simulations with synthetic and real data show that the proposed strategy leads to a significant performance improvement under spectral variability and state-of-the-art performance otherwise.

Haribadu and Bindu (2017), proposed an image fusion method based on Discrete Wavelet Transform (DWT) and visibility. In the proposed method, one level DWT applied on Gray level MRI image and color information of intensity component of PET image to get four coefficients and finally the fused image obtained after applying inverse Discrete Wavelet Transform (IDWT). The results showed that the proposed work gives good result and also improve the resolution of the image for better visual perception with respect to PSNR, MSE, Cross correlation, Mean, Standard Deviation and Entropy values.

This paper leads to fusion of hyper spectral and high resolution images based on DWT transform. For this purpose, pre-processing operations were initially applied to the hyper spectral data, and then the two sets of data were registered. The GST algorithm were applied to fusion scheme and the DIV, CC, Q and RMSE indexes were used for accuracy assessment of final fusion. The innovation of this paper is using wavelet transform decomposition of PAN image to prominent spatial information of it and using this information for accuracy improvement of hyperspectral and high resolution image fusion. It is supposed that high accuracy results can be gained using this method.

2. Materials and Methods

2.1 Satellite Imagery and Study area

EO-1/ Hyperion is the first hyper spectral satellite in the new millennium launched by NASA in Nov. 21, 2000. Hyperion data can now be acquired from the USGS EROS data center (Figure1). OrbView-3 is a high-resolution imaging mini-satellite owned and operated by orbital imaging corporation (ORBIMAGE), which is a commercial provider of earth imagery acquired from family of imaging satellites (Figure2). Table (1), shows the technical information of used data.

Table1. Tabulation of data for used images

Satellite-Sensors	Spatial Resolution (meter)	Spectral Range (nanometer)	Band Number
EO-1 - Hyperion	30	400-2500	242
OrbView-3 panchromatic	1	450-950	1

Figure1. Hyperion Image

Figure2. OrbView-3 Image

Because the data used for image fusion must be acquired from one scene in the same or the nearest time, such relevant data from Washington city of United States of America was found. This area is located at $38^{o}\ 50^{'}$ N and $77^{o}\ 00^{'}$ W to $38^{o}\ 54^{'}$ and $77^{o}\ 03^{'}$ geographic latitude and longitudes.

2.2 Data Preparation

Co-registration of two images has been done using the high-resolution image (OrbView-3 pan) as master and Hyperion as slave. The amount of RMSE in the registration processes was about 0.83 RMSE. The final pixel size of 4 meter was used to fit two dataset. This spatial resolution was chosen based on SF (ratio of high spectral resolution pixel size to high spatial resolution pixel size), method. After preparation of images, the DWT decomposition applied on PAN image and results fused with hyper spectral image by GST algorithm.

2.3 Discrete Wavelet Transform (DWT)

Wavelet transform is a mathematical tool developed originally in the field of signal processing. It can also be applied to fuse image data following the concept of the multi-resolution analysis (Jagruti, 2014). The scaled and translated basis elements of the 2D wavelet transform are given by (Adelson et al., 1987). Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower frequency band and higher frequency bands. The Discrete Wavelet Transform (DWT), which applies a two channel filter band (with down sampling) iteratively to the low pass band (initially the original signal). The wavelet representation consists of the low-pass band at the lowest resolution and the high-pass bands obtained at each step. This transformation is invertible and non-redundant. In wavelet analysis, wavelet transform divides the image signal into wavelets representing each pixel of the original image as coefficients.

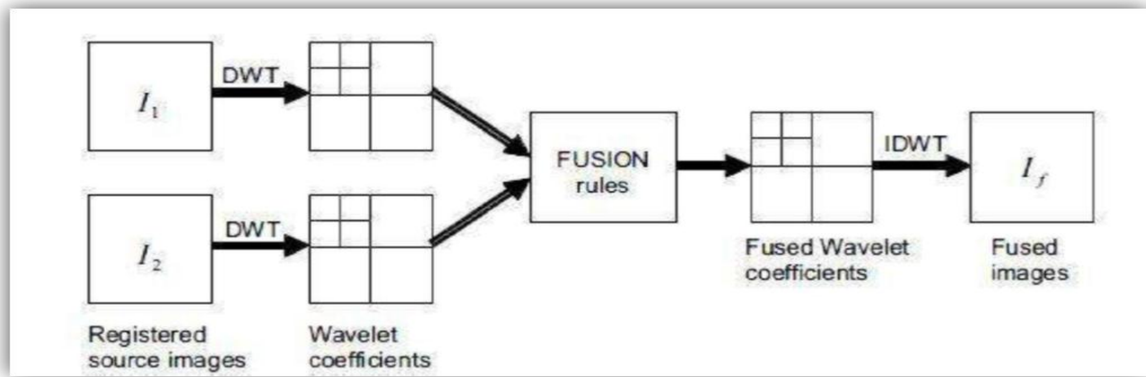

Figure3. Wavelet Transform based image fusion (Hasani Moghaddam, 2018)

The 2D image signals are broken down through layer by layer decomposition process. Four frequency bands, named (A) Low-Low, (B) Low-High, (C) High-Low and (D) High-High are obtained after first level of decomposition. The next level of decomposition is obtained by applying a recursive decomposition procedure applied to the Low-Low band of the current decomposition stage. Thus, N-level decomposition will finally result into 3N+1 different frequency bands including 3N high frequency bands and one Low-Low frequency band (Deepika and Sindhuja, 2014).

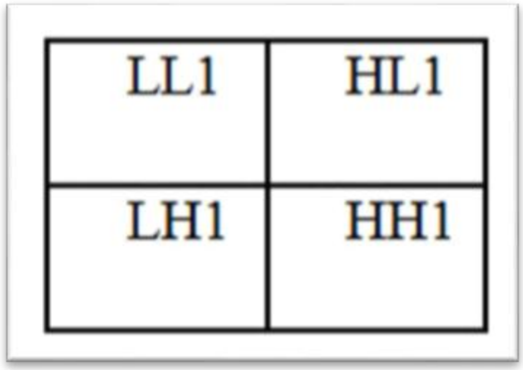

Figure4. Sub-band distribution of Discrete Wavelet Transform for level (Hasani Moghadda, 2018)

2.4 Gram-Schmit Transformation (GST)

The GS procedure makes a set of random variables uncorrelated or orthogonal to each other, assuming knowledge of the cross-correlations between them. For instance, with three random variables x_1, x_2 *and* x_3 with known correlations:

$$p_{ij} = E\left[x_i, x_j\right], ij \in [1,2,3] \quad (1)$$

This equation is obtained first.

$$\begin{bmatrix} V_2^1 \\ V_3^1 \end{bmatrix} = \begin{bmatrix} -q_2^1 & 1 & 0 \\ -q_3^1 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad (2)$$

where $q_j^1 = p_{j1} p_{11}, j = 2,3$

This operation produces random variables v_2^1 and v_3^1 which are orthogonal to x_1 but correlated with x_2 and x_3, respectively. The next step is to find a random variable which is correlated with $x_3\, x$ but orthogonal to both x_1 and x_2. This is accomplished by defining:

$$v_3^2 = v_3^1 - \frac{E\left[v_3^1 v_2^1\right]}{E\left[v_2^1\right]} * v_2^1 \quad (3)$$

The expectations on the right-hand side can be computed by cross-correlations of the original variables. The variables x_1, v_2^1 and v_3^1 are orthogonal to each other, while spanning the probability space of x_1, x_2 and x_3 the task of orthogonal the input is complete. The procedure is easily extended to an arbitrary number of random variables (Darvishi et al., 2005).

2.5 Accuracy Assessment of Fusion Method

Image fusion methods are evaluated by comparing the fused image and reference image which is assumed to be ideal. Generally, the reference image is not available in practice. Hence these methods are evaluated by comparing the original low resolution HS image and fused image (Mamatha et al., 2015).

A. Root mean square

It is a frequently used parameter to compare the difference between original HS image and pan-sharpened image by directly calculating the changes in pixel values. It is defined as:

$$RMSE = \sqrt{\frac{1}{i*h*n}\left(\sum\sum\sum(F(i,j)-H(i,j)\right)^{2}} \qquad (4)$$

$i*h*n$ represent the size of the fused image. H(i, j) is the pixel value of HS image and F (i, j) is the pixel value of fused image at i, j location .

B. Correlation Coefficient

It measures the similarity of two images. It ranges from -1 to +1. +1 indicates that two images are highly similar and -1 indicates highly dissimilar. It is calculated as:

$$CC(\mathrm{F},H) = \frac{\sum(F-\overline{F})(H-\overline{H})}{\left(\sum(F-\overline{F})^2)(\sum(H-\overline{H})^2\right)} \qquad (5)$$

F, H represent fused image and Hyper spectral image.

C, Universal Image Quality Index (Q)

It is calculated as:

$$Q = \frac{4\sigma_{fh}\overline{FH}}{\sigma_f^2\sigma_h^2\left(\overline{F^2}+\overline{H^2}\right)} \qquad (6)$$

Where $\sigma_{f\mathrm{h}}$ is covariance between fused image and HS image. $\sigma_h^2 and \sigma_f^2$ are variance of HS and fused images respectively and $\overline{H}, \overline{F}$ are mean of HS and fused images respectively.

D. Differences in variances (DIV):-

It is calculated as:

$$DIV = 1 - \frac{\mathrm{var}iance\left(Fused\ \mathrm{Im}age\right)}{\mathrm{var}iance\left(Original\ \mathrm{Im}age\right)} \qquad (7)$$

3. Results and Discussion

The result of image fusion based on DWT decomposition showed that implementation of DWT coefficient on PAN image have a high accuracy in terms of hyper spectral and high-resolution images fusion. Spatial quality evaluation of the fused image is a complex task usually based on perceptual inspection. It can be clearly observed from the fused images as all the image fusion methods sharpen the respective hyper-spectral bands. Regarding the preservation of spatial resolution, all discussed image fusion methods behave similarly. However, a greater resemblance between the panchromatic and the intensity image doesn’t mean better preservation of spatial resolution. Therefore, RMSE method is used for solving this issue. Due to the high correlation between the visible bands, the relation between one of the fused visible wavelength range images and the high resolution band must be calculated for accuracy assessment of image. Figure (5), showed final fused image of Hyperion and Orbview-3 pan images based on DWT.

Figure5. Hyperion and Orbview-3 pan images fusion based on DWT

DIV, CC, Q and RMSE methods applied on fused image for accuracy assessment of it.

Table2. Accuracy assessment

	DIV	CC	Q	RMSE
Fused Image	0.0406	0.920	0.854	2.438

Based on the results, it can be clearly observed that the DWT based fusion technique has high accuracy. In all of the accuracy assessment methods, fusion images have high results and it showed the high quality of fused images in terms of spatial and spectral feature presentation.

4. Conclusions

The image fusion methods are used to generate high resolution images that attempts to preserve the spectral characteristics of the original data. There are no generalized criteria for the selection of a particular fusion technique. The selection of the fusion method for an application depends largely on the dataset. For image fusion methods, spatial enhancement and spectral preservation are all critical issues. In this paper, DWT based hyper spectral and high-resolution image fusion was used and its performance evaluated by several accuracy assessment methods was shown. Applying the DWT coefficient on PAN image, preserve its spatial detail as well as the original image. This method in terms of hyper spectral and high-resolution image fusion, preserve high frequency information beside of low frequency information.

Spectral and spatial information may be changed during fusion role, but by the use of DWT based image decomposition, this feature is transformed to fused images and showed in results. The results of this study were approved by (Mamatha et al., 2015), and (Bopche and Gade, 2018).

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