Assessment of Multisource Remote Sensing Image Fusion by several dissimilarity Methods

Feiyuan Li*

1Investigation Department, Shandong Police College, Jinan, Shandong, 250000, China
2Police Technology and Equipment Innovation Research Center, Shandong Police College, Jinan, Shandong, 250000, China
*Corresponding author’s e-mail: lfy@sdpc.edu.cn

Abstract. Recently, advancements in remote sensing technology have made it easier to obtain various temporal and spatial resolution satellite data. Remote sensing techniques can be a useful tool to detect vegetation and soil conditions, monitor crop diseases and natural disaster prevention, etc. Although the same scene taken by different sensors belong to the same ground object, the information that they offered are redundant, complementary and collaborative due to the spatial, spectral and temporal resolution are different. The method of image fusion can integrate an image with rich details and valuable information from multi-source remote sensing images, which aim to obtain more comprehensive and precise observations of the ground object. By using aspects from multi-source image fusion, this review presents the current status and future trends in remote sensing image fusion. First, different image properties and their applications are presented for remote sensing datasets at home and abroad. Second, a general summary and inductive analysis of the challenging difficulty of different types of multisource image fusion methods is conducted. Third, experiments are tested on eight different methodological approaches, and experimental results demonstrate that GSA method is the best alternative in terms of obtaining high spatial resolution and retaining the spectral information.

1. Introduction
The aim of remote sensing is to capture the image with complicated spatial information about Earth’s ground objects. There are many applications that simultaneously require our desired spectral, spatial, and temporal information in a signal image such as target detection, classification task and so on. In order to generate a high-quality map, the fusion of Panchromatic and Multispectral/Hyperspectral images is significant. The fused image contains more valuable and informative details than any of the original images. Functions of the different remote sensing sensors have different emphases. For example, multispectral imaging (MSI) can provide relatively detailed spectral information, and Panchromatic (PAN) image have high spatial resolution. And after image fusion, it is possible to combine these complementary information and produce an image with both high spectral and spatial resolution, which also called pansharpening [1]-[3].

Recently, there are many algorithms for pansharpening, which can be broadly classified into the following four classes: Component substitution (CS), Multiresolution analysis (MRA), Bayesian and Variational optimization (VO) method [4]-[5]. In these works, CS methods including principle component analysis (PCA), intensity-hue-saturation (IHS) and Gram-Schmidt (GS), which is characterized by substituting a component that is obtained by a spectral transformation of the MS bands with the PAN image [6]-[7]. The MRA-based algorithm often employs wavelet transform,
Laplacian pyramids, and Curvelet to extract spatial details of the PAN image, afterwards, the spatial details is injected into the up-sampled MS bands [8]. Beyond that, other mixed-method such as Guided Filter PCA (GFPCA) [9]-[10] which uses component substitution and MRA simultaneously have been proposed by researchers. The Bayesian framework can incorporate both a prior knowledge and the observed multispectral and PAN data, however, Bayesian method replies on the posterior distribution [11]. Variational Inference methods are related to Bayesian methods, which is achieved by maximizing the posterior probability density of the PAN image to estimate the target image [12].

High-resolution satellite images are now accepted as a necessary tool that provide abundant urban ecological research resources. Pansharpened GF-2 and GF-6 MFV imagery are Chinese high-resolution remote-sensing satellite with 1 m resolution and 16 m resolution, respectively. The GF-6 MFV offers 8 multispectral bands, which could be a useful supplementary data for GF-2. The high spatial resolution of GF-2 and the 8 spectral bands of GF-6 offer more possibilities of extracting additional information of ground observation. Therefore, it is necessary to fuse these two data to compare different pansharpening methods and select the more suitable one. The objective of this paper is to compare different pansharpening methods by using qualitative and quantitative analysis and recommend the most satisfactory approach with minimum spectral and spatial distortions for multisource GF image fusion.

2. Image fusion techniques

2.1. CS fusion technique

CS-based method first extends MSI by the interpolation to size PAN image, then \( I_L \) is obtained by the calculating formula of intensity component, and histogram matching is used to normalize the intensity distribution. Finally, detailed information is injected according to the formula (1):

\[
\hat{M}_k = \bar{M}_k + g_k (P - I_L)
\]

Where \( k \) is the \( k \)th multispectral band, and \( k = 1, ..., b \). \( g = [g_1, g_2, ..., g_b] \) represents vector weight parameters. \( P \) is the original Pan image. Intensity component \( I_L = \sum_{i=1}^{b} \alpha_i \bar{M}_i \), where \( \alpha \) is a weight vector.

The advantages of CS-based method could be done as follows: the fusion image has the high spatial fidelity to the original image; the algorithm is very fast and easy to implement; it is robust to the impact of registration errors to a certain degree. However, spectral distortion is produced when the spectral mismatch between Pan and MSI is present. PCA and GS are among the most representative of CS-based approaches [13].

2.2. GFPCA fusion technique

GFPCA is a hybrid model which combine the strengths of different methodologies. Different from CS-based method, GFPCA uses high resolution Pan image to perform guided filter, which can not only preserve the original spectral information with a lower spectral distortion, but also integrate spatial structural information from Pan image. In order to improve the processing speed, PCA is applied to separate information content from noise with its decorrelating property, because the first \( i \ll b \) principal components contain most information of MSI. The process of denoising is used because the guided filter will increase noise and computational cost.

Imagine that Pan image \( P \) is the guided image, \( PC_i(i \ll b) \) is the \( i \)th principal components of the MSI \( \bar{M} \). Then the filtered output \( PC_i \) can be represented by the affine transform of \( P \):

\[
PC_i = \mu_j P + \nu_j, \quad \forall i \in \omega_j
\]
where $\omega_j$ is a local window with $(2d+1) \times (2d+1)$. And the values of the coefficient $\mu_j$ and $\nu_j$ are decided by the following loss function:

$$C(\mu_j, \nu_j) = \sum_{i=1}^{m} [(\mu_j P + \nu_j - \text{PC}_i)^2 + \varepsilon \mu_j^2]$$

(3)

where $\varepsilon$ is a regularization parameter. The value of $\mu_j P + \nu_j$ is get closer to the $\text{PC}_i$ term by the loss function to ensure the preservation of the original spectrum information.

2.3. CNMF fusion technique

Coupled Nonnegative Matrix Factorization (CNMF) can be exploited for fusing low-spatial-resolution hyperspectral image (HSI) and high-spatial-resolution MSI to achieve both high spatial and spectral resolution image [14]. Assuming that the spectrum in a given pixel is a linear combination of these spectra endmembers, then $X = HU$, $X \in \mathbb{R}^{p \times n}$ ($H \in \mathbb{R}^{b \times p}$ is the spectral feature of endmembers, $U \in \mathbb{R}^{p \times n}$ is an abundance matrix). The multispectral and hyperspectral data are substituted into the following formula:

$$X_h \approx H_h U_h, \quad X_m \approx H_m U_m$$

(4)

Where $H_h$ and $H_m$ are the endmember matrix of HSI and MSI, respectively. $U_h$ and $U_m$ are the abundance matrix of HSI and MSI, respectively. $H_h$ is initialized by Vertex Component Analysis (VCA) [15]. $H_h$, $U_h$, $H_m$ and $U_m$ are optimized alternately using multiplicative update rules introduced by Lee and Seung [16]. Considering that CNMF algorithm is used to fuse MSI and Pan image in this paper, only $U_m$ is varied while $H_m$ is kept constant during optimization. The final fusion image is obtained by $H_h U_m$.

3. Analysis and discussion

The experimental data used in this paper is GF-6 MFV image and GF-2 Pan image. Figure 1 gives the fusion results of two real satellite images. The original MFV image size is $50 \times 50$ pixels in Figure 1(a), and the size of the original Pan image is $800 \times 800$ in Figure 1(b). MFV image has 8 bands. From Figure 1, we can see that GFPCA best preserves spectral information, but a blur effect occurs reflecting the loss of spatial details. PCA and GS methods improves the contrast in the reconstructed image, however, a spectral distortion take place. Especially, the spectral information is not retained in CNMF method seen as Figure 1(h) due to CNMF is based on spectral unmixing which is easy to result in spectral degradation via mixed pixel decomposition. The ability of SFIM to maintain spatial details is poor, which lose most spatial information. GSA method shows the best overall performance considering the combination of spectral and spatial information, which can increase spatial details while preserving spectral information.
Figure 1 Experimental results of different methods on GF satellite data: (a) MVF image of GF-6, (b) GF-2 Pan image, (c) PCA, (d) GS, (e) GSA, (f) SFIM, (G) GFPCA, (h) CNMF, (i) MTF-GLP

A quantitative analysis on different methods with numerical results are presented in Table 1. The measure of CC shows that GS method performs the best and is followed by PCA, and PCA performs best for SAM. GSA has the best performance in both RMSE and ERGAS indicators, which remains generally consistent to visual observation in Figure 1.

| Method   | CC      | SAM     | RMSE   | ERGAS  |
|----------|---------|---------|--------|--------|
| PCA      | 0.82170 | 0.12414 | 0.01823| 0.21000|
| GS       | 0.82172 | 0.12422 | 0.01825| 0.21026|
| GSA      | 0.77417 | 0.13193 | 0.00409| 0.04703|
| SFIM     | 0.43485 | 0.12474 | 0.02667| 0.30707|
| GFPCA    | 0.52181 | 0.13503 | 0.00480| 0.05469|
| CNMF     | 0.81137 | 0.12449 | 0.08006| 0.92980|
| MTF-GLP  | 0.66656 | 0.12367 | 0.01527| 0.17591|
| MTF-GLP-HPM | 0.66681 | 0.12512 | 0.01529| 0.17624|

Table 2 shows the fusion results of an additional group of GF-2 Pan image and GF-6 MSI. GSA shows the best performance of three evaluated methods, with CC of 0.87205 and ERGAS of 0.03054. These results are consistent with the results of the previous experiment.

| Method   | CC      | SAM     | RMSE   | ERGAS  |
|----------|---------|---------|--------|--------|
| PCA      | 0.84931 | 0.08143 | 0.01847| 0.21655|
| GS       | 0.84914 | 0.08149 | 0.01848| 0.21672|
| GSA      | 0.87205 | 0.08516 | 0.00261| 0.03054|
| SFIM     | 0.35640 | 0.08198 | 0.02395| 0.28032|
| GFPCA    | 0.51696 | 0.09703 | 0.00349| 0.04043|
4. Conclusion

The fusion of multisource remote sensing image is an important area for providing spectral information while acquiring spatial information. Remote sensing image fusion on pixel level is focused in this paper. The performances of eight state-of-the-art pansharpening algorithms for GF-2 and GF-6 image were assessed using visual inspection and quality indices (CC, SAM, RMSE and ERGAS) with two different datasets. Some conclusions can be drawn based on the results of the contrasting methods. CS method has simple implementation and fast running speed, but the spectral information is more prone to distorted. The advantage of MRA method (such as SFIM and MTF-GLP) is spectral and temporal coherence but with high complexity. It is GSA algorithm with best performance among the eight algorithms on both datasets. GSA can improve fusion results by increasing both spatial and spectral resolution. Therefore, we are heading in our future work on classification task based on GSA algorithm.

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