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Fusion of Remote Sensing Images Using Improved ICA Mergers Based on Wavelet Decomposition

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Abstract

Spectral distortion is one of the most significant problems in the field of remote sensing image fusion. In former studies, we found the fusion method based on independent component analysis (ICA) could solve this problem effectively, and attain a better balance between spectral and spatial information of fused image. However, this method may lead to spectral distort in a few local regions unavoidably. In this paper, an improved ICA fusion method is proposed. Improvement mainly includes two aspects. Firstly, a convenient way which uses negentropy to measure the nongaussianity of IC is presented to select main body independent component (MBIC); secondly, in order to avoid too much spatial information caused by replacing MBIC with panchromatic (PAN) image directly, a wavelet decomposition is applied to extract the detail information of PAN image. The results show that the proposed method can have a better trade-off between spectral and spatial information. Moreover, compared with ICA fusion method, it can not only improve the spatial resolution of fused image, but also eliminate the drawback of spectral distortion of ICA fusion method in some local regions.

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Keywords: Image fusion; Independent component analysis (ICA); Wavelets; principal component analysis (PCA);

1. Introduction

Remote sensing has proven to be powerful tools for the monitoring to earth surface at a global, region, and even local scale [1, 2]. This is made possible by a great deal of data acquired by different types of sensors. Each sensor has its properties uniquely, especially in optical remote sensing. With physical and

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technological constraints, some satellite sensors supply the spectral bands needed to distinguish features spectrally but not spatially, while other satellite sensors supply the spatial resolution for distinguishing features spatially but not spectrally. For many applications the information provided by individual sensors are incomplete, inconsistent, or imprecise. Additional sources may provide complementary data, and fusion of different information can produce a better understanding of the observed site, by decreasing the uncertainty related to the single sources.

It is the aim of image fusion which integrates different data to obtain more information than that derived from each of the single sensor data alone "1+1>3"[3]. In the past few years, many image fusion methods have been proposed, such as hue-saturation-intensity (HSI)[4], hue-saturation-value (HSV)[5], Brovey transform (BT), principal component analysis (PCA)[6] and wavelets[7,8]. Although these methods (HSV, HIS and PCA) can provide superior visual high spatial resolution synthesized images, they distort spectral characteristics of the multispectral (MS) image obviously. For wavelets, it can control how much spatial detail or spectral information should be retained through multiscale decomposition. However, it needs human intervention to determine a better decomposed level owing to various resolution ratios between the PAN and MS images.

In former studies, we found that image fusion method based on independent component analysis (ICA) [9] could retain higher spatial and abundant spectral information simultaneously. However, all independent components (ICs) carry more or less spatial information of image. Therefore, replacing the main body IC (MBIC) with PAN image can lead to spatial information redundancy to a certain extent, which will affect the quality of fusion results. For this reason, an improved ICA fusion method is presented in current study. First, a new strategy which uses negentropy to measure the nongaussianity of IC is introduced to select MBIC. Then, using wavelet decomposition to execute the detail extraction phase, and the inverse ICA procedures to inject the spatial detail of the PAN image into the MS one.

2. Methology

2.1. ICA

ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. The latent variables are assumed nongaussian and mutually independent and they are called the independent components of the observed data[10]. These independent components can be found by ICA. ICA was initially introduced by Herault et al [11]. The estimation of the data model of ICA is usually performed by formulating an objective function and then minimizing or maximizing it. In this study, a fast algorithm called FastICA[12] using kurtosis is applied.

2.2. Determine main body IC

In former studies[9], we found that three ICs of a color image represents its main body, spectral and spatial detail information respectively. As both **S** and **A** are unknown, ICs are not necessarily arranged in order of information significance. Therefore, the ICs generated by the FastICA in different runs generally appear in different orders. Furthermore, with $\boldsymbol{X}$ having been prewritten, the sign of ICs would change in different runs, even if the order of ICs has not been changed. Although MBIC can be selected by analysis the mixing matrix **A**, it is complicated and cannot determine the order of ICs.

Nongussian is independent. The more "random" the variable is, the large its entropy[10]. A fundamental result of information theory is that a gaussian variable has the largest entropy among all random variable of equal variance. This shows negentropy can be used as a measure of nongaussianity. In this paper, we introduce negentropy to measure the significance of ICs. The lager the negentropy of IC is, the more significant that IC. The approximating negentropy is computed as following:

$$J(y) \approx \frac{1}{12}\mathrm{E}\{y^3\}^2 + \frac{1}{48}\mathrm{kurt}(y)^2 \tag{1}$$

2.3. Improved ICA fusion method based on wavelet transform

Although MBIC contains the main body content of color image, the spectral and spatial information of the color image is not completely separated. The rest ICs also carry some spatial information. Therefore, the ICA fusion method tends to present more spatial detail information than what the MS image would have if it collected with the spatial information of the PAN image. This superfluous spatial information not only improves the spatial resolution of fused image, but also may lead to spectral distortion in some local regions.

Instead of replacing MBIC with the PAN image, we could introduce in these components just the spatial detail of the PAN image that is missing in the MS image. This is the central idea of the improved ICA fusion method. Figure 1 outlines the general procedure to fuse MS and PAN images using the improved ICA method based on wavelets, and the whole procedure can be summarized as follows:

1) Register a low-resolution MS image to a PAN image, and connect rows end to end to form a new row vector in each band of the MS or PAN images.
2) Perform the FastICA on the vectors of the MS image, and obtain its ICs and mixing matrix A.
3) Select the MBIC using the method described in section 2.2
4) Generate a new PAN image whose histogram matches that of the MBIC.
5) Apply the wavelet decomposition to the MBIC and to the corresponding new PAN using the Haar wavelet. Then the approximation image (LL) and the detail images (HL, LH and HH) are attained. The decomposition level is determined according to the spatial resolution ratio of the PAN and MS images. The smaller the ratio is, the deeper the decomposition level needs.
6) Insert the spatial information of the PAN into MBIC to generate new MBIC, and then perform inverse ICA transform to produce a fusion image.

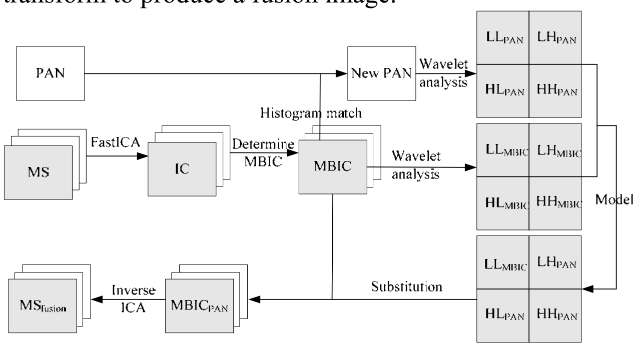

Fig. 1. Work flow of the improved ICA fusion method.

3. Case study

The IKONOS data were selected, which were acquired on 7 June 2006. The site was located in Nanjing, Jiangsu province, China. The images are composed of the MS bands 1, 2, 3 and 4 with a spatial resolution of 4 m, and a PAN band that corresponds to the spectral range of the MS bands 2, 3 and 4 has a spatial resolution of 1 m. After registering it geometrically onto the PAN image, the composite image also has a spatial resolution of 1 m. A subimage of 400×400 pixels has been considered. Figure 2(a) is the false color composite image of band 4, 3 and 2; figure 2(b) shows the IKONOS PAN image.

Fig. 2. IKONOS data from the Nanjing area on 7 June 2006; (a) MS image (bands 4, 3 and 2); (b) PAN image.

In order to examine the performance of the proposed image fusion method, we compare it with other fusion methods, such as HSV, PCA, wavelets and ICA. The fusion results of IKONOS data are shown in figure 3. Figure 3(a-b) are the fusion result of HSV and PCA respectively; figure 3(c-e) are the fusion result of wavelets with decomposition level 1 (WL1), 2 (WL2) and 3 (WL3); figure 3(f) is the fusion result of ICA; and the figure 3(g) is the fusion result of proposed method.

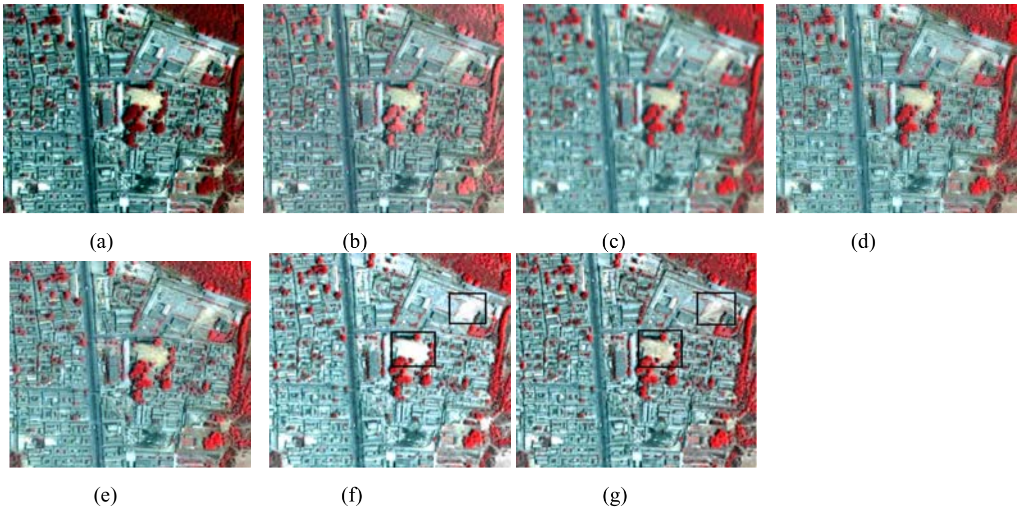

Fig. 3. The results of different fusion methods using IKONOS data (a) fused image by HSV ; (b) fused image by PCA; (c-e) fused image by WL1, WL2 and WL3 respectively; (f) fused image by ICA; (g) the fusion result of applying the proposed method.

4. Discussion and conclusion

4.1. Visual evaluation

Visual evaluation provides an overall impression of the detailed information and the similarity of the original and fused images. As shown in figure 3, each fusion method can more or less retain high spatial while preserving spectral characteristics. The HSV method (figure 3(a)) preserves the most spatial detail but distorts the spectral characteristics obviously. Unlike HSV, the PCA method (figure 3(b)) preserves fewer details. For wavelets, the fused images (figure 3(c-e) retain higher spatial resolution but less spectral information with the increase of decomposition level. Because the spatial resolution ratio between PAN and MS images is 1:4, the blocking effects appear in WL1 and WL2 (figure 3(c-d)), and attain a clear fused image in WL3 (figure 3(e)).Compared with the former fusion methods, the obvious advantage of ICA method (figure 3(f)) is that the fused image can attain a better balance between spectral characteristic preservation and high spatial resolution retention. However, this method can lead to spectral distort in some local regions, as shown in black rectangle areas of figure 3(f). The improve ICA method proposed in this paper can solve this problem effectively. From figure 3(g), the black rectangle regions can preserve the spectral information of MS image better.

4.2. Quantitative evaluation

The evaluation of fused image consists of two parts, namely spectral and spatial characteristics. Only these two aspects have good performance stimulatingly, the fusion method can be said to be excellent. It well known that the RGB system matches well with the fact that the human eye is strongly perceptive to red, green and blue primaries. Unfortunately, the RGB, cyan–magenta–yellow (CMY), and other similar color models are not well suited for describing colors in terms that are practical for human interpretation[13]. HSI color space decouples the intensity component from the color-carrying information (hue and saturation) in a color image, and the I component, which results from the mean of three bands of a color image, represents the mean spatial information of color image. As a result, it is an ideal tool for quantitative evaluation of the quality of fused image. The fused images are converted from RGB to HSI color space firstly. Then, some statistical methods, including mean and correlation coefficient (CC), are applied to describe their quality. The higher the value of the CCs of H and S are, the more similar the color information of the fused images is to the corresponding original MS image; and the higher the value of the CCs between the I components of the fusion results and the PAN image is, the higher spatial resolution the fused images have.

Table 1. The means of original and fused images in HIS color space

band	Original image	HSV	PCA	WL1	WL2	WL3	ICA	Improved ICA
H	133	110.3	133.9	132.8	132.3	132.8	134.7	129.8
I	139.2	107.3	139.2	139.3	139.2	139.2	157.9	138.9
S	54.6	94	45	55.5	55.7	56	55.9	59.4

Table 1-2 show the statistical properties of the fused image and original MS image in HSI color space. Table 1 presents theirs mean character. Table 2 shows the CCs between the fusion results and the MS image, and I components of the fusion images and the PAN image. From table 1, the three means of fused image based on HSV has the biggest derivation from those of original image in HSI color. For PCA and ICA methods, the means of former S component and latter I component have a big difference from original image. In addition, the rest methods keep the means of those of original image well.

Table 2 reveals that how much color information of the original MS image and spatial information of PAN image is preserved by the fusion methods. Although the CCs of S and I of HSV are high, it has least CC of H, and taking into account its means. Therefore, HSV has the largest color distortion. With the increase of wavelet decomposition level, the CCs of H and S components decrease inversely. This shows that the fusion image loses more spectral information when the wavelet decomposition is to a deeper level. The fusion result has a high CC of I component when it has a low CC of PAN, and vice versa. WL1 has the highest CC of I component, but the lowest CC of PAN. That is, it preserves the most spatial information of the original MS image, and the least of PAN image. Therefore, WL1 has the lowest spatial resolution. ICA fusion method can have a better balance between spectral and spatial information, its CCs of H, S and PAN are 0.75, 0.85 and 0.95 respectively. Compared with ICA fusion method, the improved

ICA fusion method not only retains abundant color information, but also enhances spatial information (CC 0.97); else, it retains the means of original image better (table 1).

Table 2. The CCs between fused images and original images.

band	HSV	PCA	WL1	WL2	WL3	ICA	Improved ICA
H	0.30	0.74	0.82	0.69	0.61	0.75	0.76
S	0.89	0.62	0.90	0.79	0.71	0.85	0.81
I	0.81	0.73	0.89	0.82	0.79	0.76	0.75
PAN	0.97	0.96	0.84	0.91	0.97	0.95	0.97

In this paper, an improved ICA image fusion method is presented. Improvement is mainly embodied in two aspects. Firstly, a convenient way which uses negentropy to measure the nongaussianity of IC is proposed to select MBIC; secondly, in order to avoid too much spatial information caused by replacing MBIC with PAN image directly, a multiresolution wavelet decomposition is applied to extract the detail information of PAN image. The INKOS image was used to show the performance of the proposed method. The results show that the proposed method can preserve abundant spectral information and higher spatial resolution, and has a better trade-off between them. Besides, it can effectively eliminate the drawback of spectral distortion of ICA fusion method in some local region.

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