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A New Technique for Multispectral and Panchromatic Image Fusion

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Abstract

In this paper, a technique is presented for the fusion of Panchromatic (PAN) and low spatial resolution multispectral (MS) images to get high spatial resolution of the latter. In this technique, we apply PCA transformation to the MS image to obtain the principal component (PC) images. A NSCT transformation to PAN and each PC images for N level of decomposition. We use FOCC as criterion to select PC. And then, we use the relative entropy as criterion to reconstruct high-frequency detailed images. Finally, we apply inverse NSCT to selected PC's low-frequency approximate image and reconstructed high-frequency detailed images to obtain high spatial resolution MS image. The experimental results obtained by applying the proposed image fusion method indicate some improvements in the fusion performance.

Keywords: Image fusion, fourth-order correlation coefficient (FOCC), multispectral remote sensing, nonsubsampled contourlet transform (NSCT), relative entropy.

1. Introduction.

Image fusion can produce fused images that are more suitable for human vision perception, object detection, and automatic target recognition [1]. The injection of detail information from high spatial resolution PAN image into the low spatial resolution MS image can enhance the resolution of MS image, and this process is known as pan-sharpening. In the past, some pan-sharpening methods applying multi-resolution approaches are proposed, they use discrete wavelet transform (DWT) [2], [3], Laplacian pyramid [4], or à trous wavelet transform [5] to images, and the detail spatial information from the PAN image is injected in the MS image. In recent years, some approaches [6], [7] use the intensity–hue–

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saturation (IHS) transformation or principal component analysis (PCA) transformation to MS images before pan-sharpening to solve the problem of high correlation among the spectral bands. Among these methods, literature [6] selects the first principal component (PC1) to instead of MS images. However, it is not based on any statistics between the high resolution PAN image and the low resolution PC1 image [7]. To overcome this problem, literature [7] uses cross-correlation coefficient (CC) as the criterion and selects PC with highest absolute CC with PAN image to instead of MS images. However, all of them didn't consider PC' high-frequency detailed images and only use PC' low-frequency approximate image instead of PAN's in the pan-sharpening process. Different surface feature has different sensitivity in the different spectrum. This is one of the major characteristics of MS image. Therefore, if we don't consider PC' high-frequency detailed images, the fused image will loss some detail information of MS image. To overcome this problem, we use relative entropy as the criterion to reconstruct high-frequency detailed images from PC's and PAN's. Experimental results show that our fused image obtains a high spatial resolution and higher similarity with the referenced true high resolution MS image than other approaches.

2. Basic concepts

2.1. Principal component analysis (PCA) transformation

PCA is a linear transformation of the multidimensional data. The data are transformed to a new coordinate system such that the first coordinate represents the largest variance (the first principal component) by any projection, the second coordinate to the second largest variance, and so forth. For more details, refer to [8].

2.2. Nonsubsampled contourlet transform (NSCT)

NSCT is an improved contourlet transformation (CT). The original contourlet is constructed by the combination of laplacian pyramid (LP), which is first used to capture the point discontinuities, and the directional filter banks (DFB), which is used to link point discontinuities into linear structure. For more details, see [9].

2.3. FOCC

We can use the cross-correlation coefficient (CC) to measure the similarity between two images, and it is defined as

$$CC(A|B) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j}-\overline{A})(B_{i,j}-\overline{B})}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j}-\overline{A})^2(B_{i,j}-\overline{B})^2}} \tag{1}$$

Where $M \times N$ is the image's size, $\overline{A}$ and $\overline{B}$ are the mean of images A and B.

However, it has been demonstrated that the higher order moments have several advantages over second-order moments [10] [11]. Thus, we can use fourth-order correlation coefficient (FOCC) to measure the similarity between two images instead of CC. It is defined as

$$FOCC(A|B) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j}-\overline{A})^2(B_{i,j}-\overline{B})^2}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j}-\overline{A})^4(B_{i,j}-\overline{B})^4}} \tag{2}$$

2.4. Relative entropy

Considering a W×W window around the (i, j)th element of the matrix in the image. In this window, the probability of a pixel xn is pn=xn/S. We call such a probability model the data model P. In the model P, a pixel's Shannon's information content is defined as

$$I_P(x_n) = -\log p_n = -\log(x_n / S) \tag{3}$$

$$S = \sum_{n=0}^{W \times W} x_n \tag{4}$$

We can assume another probability model called model Q which uses a uniform distribution for this group of pixels. The probability of pixel xn is qn=1/N. The relative entropy [12], is defined as

$$D(Q,P) = \sum_{n=0}^{N-1} q_n \log \frac{q_n}{p_n} = \frac{1}{N} \sum_{n=0}^{N-1} (\log A - \log x_n) = \log \frac{A}{G} \tag{5}$$

$$G = \exp[(1/N) \sum_{n=0}^{N-1} \log x_n] \tag{6}$$

Where A=(S/N) is the arithmetic mean， and G is the geometric mean. A small (large) value of the relative entropy D(Q, P) indicates a relatively good (poor) fit of the model Q to the data. In other words, we can use the relative entropy to measure the smoothness of the data.

In this paper, we can calculate each pixel's D(Q, P) to judge it weather is detail information or not. In smooth areas the values of D(Q, P) are close to zero and in areas with strong edges or textures the values of D(Q, P) are significantly larger than zero [12].

We assume a pixel at location [x, y], its relative entropy is d0(x, y), and calculate each pixel's d0. To overcome the problem that d0 is potentially sensitive to noise in dark areas, we calculate the relative entropy, denoted d1 for the "negative image" given by x1[x, y]=M-x[x, y]. And then, we define d(x, y)= d0(x, y)×d1(x, y) as the criterion to measure each pixel's detail information.

3. Image fusion algorithm

The steps of proposed fusion algorithm are as follows.

a. The low resolution MS images are resampled to the scale of the high-resolution panchromatic image.

b. We apply PCA transformation to the MS image to obtain the principal component (PC) images (because MS image has high correlation among the neighboring pixels both spatially and spectrally)

c. PAN image and PC images are normalized (In=I/255). And then, NSCT transformation to normalized images for 3 level of decomposition to obtain each image's low-frequency approximate image and high-frequency detailed images.

d. We calculate the FOCC between PAN's and each PC's low-frequency approximate images, and select the PC having the highest value of FOCC.

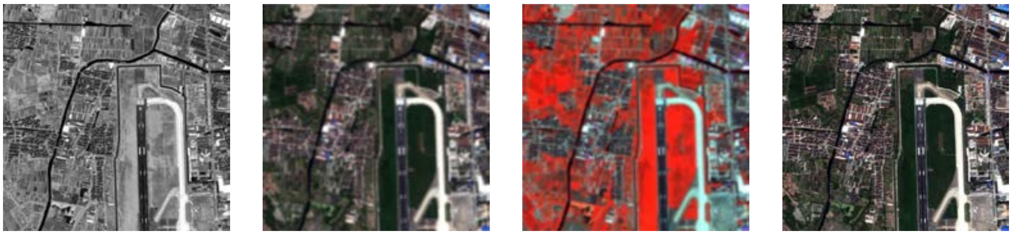
e. We calculate each pixel's d in PAN's and selected PC's high-frequency detailed images. And then, we compare with each pixel's d between PAN's and selected PC's high-frequency detailed images, and select the pixel with higher d (e.g. if a pixel at location [x, y], and PAN's d(x, y) higher than PC's d(x, y), PAN's pixel will be selected) to reconstruct high-frequency detailed images.

f. We apply inverse NSCT to selected PC's low-frequency approximate image and reconstructed high-frequency detailed images to obtain fused image. Finally, the fuse image is multiplied by 255 (Inverse normalization) to obtain the ultimate high spatial resolution fused image.

4. The result of simulation and comparison

In this paper, we use QuickBird images to evaluate the performance of our method and to compare with the method comes from literature [6] (denoted as PCA-WDT) and the method comes from literature [7] (denoted as APCA-NSCT).

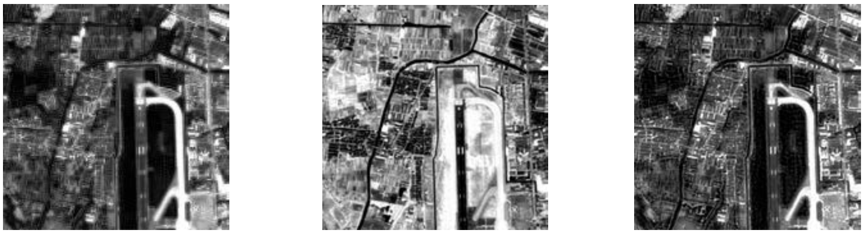
Fig.1 (a) shows the 512×512 pixel QuickBird high-resolution (2.8 m) panchromatic image of Shanghai, China. Fig.2 (b)-(c) shows the corresponding 512×512 pixel low-resolution (11.2 m) QuickBird MS images after resampling to the same size of the high-resolution panchromatic image using cubic interpolation. Fig.2 (d) shows the 512×512 pixel referenced true high-resolution (2.8 m) MS (RGB bands) image.



(a) (b) (c) (d)

Fig.1. (a) High-resolution (2.8 m) PAN image. (b) Resampled low-resolution (11.2 m) RGB bands. (c) Resampled low-resolution (11.2 m) NIR–GB bands. (d) True high-resolution (2.8 m) RGB bands.

Fig.2 shows fusion results by using different methods. We use the average gradient and the EMEE [13] of the images as the standard to measure image definition, and use the CC between fused image and referenced true high-resolution MS image as the standard to measure the similarity between fused image and high-resolution MS image. These indicators can be found in the Table 1.



(a) (b) (c)

Fig. 2 (a) The fused image by PCA-DWT. (b) The fused image by APCA-NSCT. (c) The fused image by our method.

The quantitative evaluation results of fused images.

	average gradient	EMEE	CC
PCA-DWT	11.5741	6.6867	0.89
APCA-NSCT	12.7870	6.8284	0.32
Our algorithm	12.6917	7.4983	0.92

As it can be seen from Fig. 2 and Table 1, our method provides a better spatial enhancement for the fused image, while its similarity with true high-resolution MS image is higher than other methods. The spatial enhancement in APCA-NSCT method is also good, however its similarity with true high-resolution MS image is poor because it didn’t consider the detail of MS image in the fusion process. Due to the drawbacks (e.g. the poor ability to represent directional details.) of DWT, the spatial enhancement in PCA-DWT method is worse than other methods.

5. Conclusions

In this paper, a technique is presented for the fusion of PAN and low spatial MS images to get high spatial resolution of the latter. Experimental results show that our fused image obtains a high spatial resolution and higher similarity with the referenced true high resolution MS image than other approaches.

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References

[1] C. Pohl and J. L. van Genderen. Multisensor image fusion in remote sensing: Concepts, methods, and application. *Int. J. Remote Sens*. 1998, 19(5): 823–854.

[2] J. Zhou, D. L. Civco, and J. A. Silander. A wavelet transform method to merge LandSat TM and SPOT panchromatic data. *Int. J. Remote Sens*. 1998, 19(4):743–757.

[3] Y. Zhang. A new merging method and its spectral and spatial effects. *Int. J. Remote Sens*. 1999, 20(10): 2004–2014.

[4] B. Aiazzi, L. Alparone, S. Baronti, and A. Garzelli. Context-driven fusion of high spatial and spectral resolution images based on oversampled multiresolution analysis. *IEEE Trans. Remote Sens*. 2002, 40(10): 2300–2312.

[5] J. Nunez, X. Otazu, O. Fors, A. Prades, V. Pala, and R. Arbiol. Multiresolution-based image fusion with additive wavelet decomposition. *IEEE Trans. Geosci. Remote Sens*. 1999, 37(3):1204–1211.

[6] M. Gonzalez-Audicana, J. L. Saleta, R. G. Catalan, and R. Garcia. Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition. *IEEE Trans. Geosci. Remote Sens.* 2004, 42(6):1291–1299.

[7] Vijay P. Shah, Nicolas H. Younan, and Roger L. King. An Efficient Pan-Sharpening Method via a Combined Adaptive PCA Approach and Contourlets. *IEEE Transactions on geoscience and remote sensing*. 2008, 46(5):1323-1335.

[8] R. Duda and P. Hart. *Pattern Classification and Scene Analysis.* New York: Wiley, Preliminary Edition.; 1996.

[9] da Cunha A L, Jianping Zhou and M. N. Do. The nonsubsampled contourlet transform: theory, design and applications. *IEEE Trans. Image Process*. 2006, 15(10):3089-3101.

[10] J. G. Proakis, C. M. Rader, F. Ling, and C. L. Nikias. *Advanced Digital Signal Processing*. New York: Macmillan; 1992.

[11] M. Welling. Robust higher order statistics. In: Proc. 10th Int. *Workshop Artif. Intell. Statist*; 2005, p. 405–412.

[12] Guang Deng. An Entropy Interpretation of the Logarithmic Image Processing Model With Application to Contrast Enhancement. *IEEE Transactions on Image Processing.* 2009, 18(5):11355-1140.

[13] Karen Panetta, Sos Agaian, Yicong Zhou and Eric J. Wharton. Parameterized Logarithmic Framework for Image Enhancement. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*. 2011, 41(2):460-473.