Fusion of multispectral and panchromatic data using regionally weighted principal component analysis and wavelet

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This study proposes a new multispectral (MS) and panchromatic (PAN) image fusion algorithm based on regionally weighted principal component analysis (RW-PCA) and wavelet. First, the MS images are segmented into spectrally similar regions based on the fuzzy *c*-means (FCM) clustering method. Secondly, based on the spectral vector's degree of membership in each region, a new RW-PCA method is proposed to fuse the MS and PAN images region by region, and fused MS images are obtained. In the traditional PCA-based fusion method, the MS and PAN images are fused globally with the same transform method. In the proposed RW-PCA-based fusion method, the local spectrum information of the MS images is employed, and the spectral information is better preserved in the fused MS images. Finally, in order to improve the quality of spectral and spatial details, the above fused MS images and the original PAN images are further fused using the wavelet-based fusion method, and the final fused MS images are obtained. Experimental results demonstrated that the proposed image fusion algorithm performs better in spectral preservation and spatial quality improvement than some other methods do.

Keywords: Fuzzy, RWPCA_WT, regionally weighted, WT.

WITH the rapid development of remote sensors and digital techniques, the fusion of panchromatic (PAN) and multispectral (MS) images, i.e. pansharpness of MS images, has aroused much attention and has been widely used in many fields[1,2] such as topographic mapping, land use and geology. Generally, the fused MS images integrate the spectral information of the source MS images with the spatial information of the source PAN image.

The component substitution methods such as intensity-hue-saturation (IHS), principal component analysis (PCA), Brovey transform (BT) and Gram-Schmidt (GS)[3–7] belong to this class of pansharpening. These methods can efficiently enhance the spatial quality of MS image, but usually cause serious spectral distortion. The PCA-based fusion method can increase the spatial quality of the MS image by substituting the first principal component with PAN image where the local spectral information changes greatly by introducing much spectral distortion into the fused MS images[8]. In IHS method, fused results show large spectral distortions, where histogram matched PAN and the intensity component do not generally have the same local mean[9]. GS method observes a significant spectral distortion when there is a local difference (spectral mismatch) between the MS and PAN image[10].

More recently, the multiscale transform tool (MST)-based fusion methods, such as decimated wavelet transform, discrete 'wavelet packet', à trous, Laplacian pyramid, curvelet and contourlet, multiresolution fusion based on super resolution methods have turned out to be effective for the PAN sharpening of MS images[11]. These methods are generally based on the same principle: to extract from the PAN image, the spatial detail information not present in the MS images and later inject it into the latter. In MST methods, the frequencies between the valid upper bound of the low frequencies in the MS images and the valid lower bound of the high frequencies in PAN images are ignored during the injection process, because the valid low-frequency sub-bands of the MS images are often disjointed with the injected high-frequency sub-band of the PAN image. This reduces the spatial quality enhancement when compared to other fusion methods[12].

Hybrid method such as à trous wavelet and PCA, combination of wavelet with HIS transform or PCA transform, non-separable wavelet frame transform (NWFT)[13], wavelet transform and sparse representation[14], ICA and wavelet decomposition[15], curvelet and IHS[16] is a combination of CS and MST methods, where the high frequency information of the PAN image is injected into the MS images and the low-frequency information of the MS images is not modified. Therefore the hybrid method-based fusion methods generally perform better in spectral and spatial preservation than the other methods[17].

This study proposes a new MS and PAN image fusion algorithm, which consists of three steps. The fuzzy *c*-means (FCM) clustering method is employed first to segment the MS image into spectrally similar regions. For each region, the MS and PAN images are fused by a new regionally weighted principal component analysis (RW-PCA) method. Finally, the above fused MS images and the source PAN image are further fused by the wavelet-based fusion method. In the proposed RW-PCA algorithm, the employed transformation matrix is constructed from local spectral information of the MS images in each region. The RW-PCA based fusion method can introduce less spectral distortion than the traditional PCA-based fusion method does. In addition, using the RW-PCA based fusion method, the low and mid-frequency components of the PAN image can be well preserved in the

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fused MS images. With the wavelet-based fusion method, the high frequency components of the PAN image are well injected into the final fused MS images and the blocking artifacts caused by segmentation can also be reduced. Several sets of experiments demonstrate that the proposed fusion method performs better in spectral preservation and spatial quality enhancement than the traditional PCA-based and the wavelet-based fusion methods.

We now propose a new MS and PAN image fusion method. The original MS images are spectrally segmented into many regions based on FCM clustering method. Then a new RW-PCA is proposed to fuse the source images region-by-region. As each kind of segmented regions has similar spectral characteristics, the proposed RW-PCA method can preserve the spectral information of the source PAN image, which can also be well injected using the proposed RW-PCA method. Finally, the fused MS images are further merged with the source PAN image using the traditional wavelet-based fusion method, in which the highest frequency information of the source PAN image is extracted by the wavelet transform and then injected into the fused MS images. The final fused MS images are then obtained.

The PCA is a simple but efficient linear transform method, by which the observed multi-channel data can be transformed into some uncorrelated components. It has been widely applied to many fields, such as face recognition[11], feature extraction[1] and image fusion[2]. Especially, when applied to fusion of PAN and MS images, it can isolate the spatial information of the MS images into the principal component and the spectral information into another different component. By substituting the first principal component with the PAN image, the fused MS images can be obtained.

In the proposed FCM clustering-based spectral segmentation method, the MS images are segmented into many similar spectral regions using the FCM clustering method, which is a commonly used unsupervized clustering method and widely applied to MS image segmentation[2]. Different from some clustering methods with hard cluster technique, the FCM clustering method allows each data point to belong to more than one cluster according to its degree of membership in each cluster. Therefore, the FCM clustering method is applied to the spectral segmentation of the MS image in this study.

The MS image is assumed to be composed of S bands and each band has N pixels. Then the MS images can be represented by a matrix $x = (x_1, x_2, ..., x_N)$ with $S*N$ order, where x_j ($j = 1, 2, \ldots, N$) is an S-dimensional column vector to represent the spectral vector of the MS images at different pixel positions. The FCM clustering can thus be accomplished by minimizing the objective function

$$j_{\mathrm{FCM}}(U, A) = \sum_{j=1}^{N} \sum_{i=1}^{C} \mu_{i,j}^{d} \| x_j - a_i \|^2, \tag{1}$$

where $U = (\mu_{i,j})$ is an $C*N$ order matrix and $\mu_{i,j}$ represents the jth spectral vector's degree of membership in the ith kind of regions. $A = (a_1, a_2, \ldots, a_C)$ is an $S*C$ order matrix. C denotes the class number and $D \in [1,\infty)$ represents the degree of fuzziness, which is set to 2 in this study. The optimum solution ($U*$, $A*$) can be obtained by iterative algorithms.

The ith kind of regions L_i, is thus obtained by searching for the spectral vectors with the maximal degree of membership in the ith kind of regions, i.e.

$$L = \{ j \mid i = \arg\max_{c=\{1,..,C\}} \mu_{c,j}^{*}, j = 1, ..., N, \tag{2}$$

where $\mu_{c,j}$ is the entry with row index c and column index j in matrix $U*$.

If the PCA-based fusion period is directly performed region by region after spectral segmentation, the spectral discontinuity among adjacent regions will also be introduced into the fused MS images. For obtaining higher spectral fidelity and lower spectral discontinuity, a new DWT-PCA is proposed. Besides the local spectral information in the current kind of regions, the spectral information in other kinds of regions is considered by using some regional weights during the computation of the transform matrix for each kind of region in the proposed RW-PCA.

As discussed previously, the MS image can be segmented into different kinds of regions by using the FCM clustering method. Moreover, every spectral vector's degree of membership in each kind of region is also provided by the degree matrix of membership U. In other words, the correlation among different spectral vectors can also be determined by the FCM clustering method. Then the proposed RW-PCA will employ the degree matrix of membership $U*$ to define the regional weights and the detailed computation is given as follows: for some kind of regions L_1, construct a weighted correlation matrix R_i

$$R_i = (1/N - 1) X W_i X^{\mathrm{T}}, \tag{3}$$

where $W_i = \mathrm{diag}\{(W_{1,1})^2, (W_{1,2})^2, \ldots, (W_{1,\mathrm{N}})^2\}$ is a diagonal matrix. Its weighting fact $W_{i,j}$ represents the contribution of the jth spectral vector to the construction of R_{i} and is defined by the degree matrix of membership $U*$.

$$W_{i,j} = \begin{cases} \mu_{i,j} / \lambda & (j = 1, ..., N, j \neq L_i) \\ 1 & (j \in L_i), \end{cases} \tag{4}$$

where the weight control constant $\lambda (\lambda \geq 1)$ is employed to adjust the contribution of other kinds of regions. According to eq. (4), the contribution of the other kinds of regions decreases with increase in the weight control constant. Then a higher spectral fidelity of fused MS images is obtained with a higher value of λ. However the overlarge value of λ also leads to spectral discontinuity due to the fact that more spectral characteristics among the adjacent regions are ignored.

The distribution of weights $w_{i,j}$ ($j = 1, \ldots ,N$) for the PCA regions where weights are dominant and the weights for the other kinds of regions are relatively smaller, are determined by the spectral similarity between the yellow coloured labelled regions and other kinds of regions.

(1) The higher the spectral similarity, the larger the weights assigned for those kinds of regions. For example, the weight for some building regions is larger than those for the plant regions.

(2) Similar to eq. (2), perform Eigen composition on R_i

$$R_j = \varphi_i \sum_i \varphi_j^t, \tag{5}$$

where $\sum_i$ is a diagonal matrix consisting of the eigen values of R_i in decreasing order and Φ is an orthogonal matrix consisting of the corresponding eigenvectors of R_i by columns.

(3) Compute the linear transformation φ_i^t of spectral vectors X_i in the current kind of region L_i, and obtain the corresponding component vectors Y_i

$$Y_i = \Phi_i^T X_i. \tag{6}$$

(4) Map the segmented regions of MS images to PAN image, and perform the gray stretch on the corresponding kind of regions in PAN image with the first principal component of Y_i (ref. 18).

(5) Substitute the first row of Y_i with the corresponding stretched PAN data p_i, and obtain the synthetic principal component matrix Y_i, region by region.

(6) Perform the inverse RW-PCA transformation φ_i on the synthetic principal component matrix, and obtain the ith fused spectral matrix $F_{\mathrm{i}} = \varphi_i Y_i$.

Steps (1)–(6) are implemented for all the spectral regions, and the fused spectral matrix F can be obtained by combining all the fused MS regions, i.e. $F = U_{i=1} F_{\mathrm{i}}$. The fused MS images are then obtained by rearranging each row of the spectral matrix MS band.

By the above RW-PCA based fusion method, the spectral characteristics of the source MS images can be better preserved into the fused MS images. Moreover, the mid-frequency component of the PAN image can be well injected into fused MS images. In order to inject high frequency components of the PAN image into fused MS images, the fused MS images obtained by the above RW-PCA method are further merged with the source PAN image by the traditional wavelet based fusion method in this subsection.

By combining the RW-PCA based fusion method with the wavelet-based one, both the spectral information of the source MS images and the spatial transformation of the source PAN image can be well preserved in fused MS images.

To verify the availability of the method, we use PAN and MS data as the datasets, and perform image fusion experiments. The MS image consists of three bands, i.e. red (R), green (G) and blue (B) bands, whose spatial resolutions are 5.8 m per-pixel. The spatial resolution of the PAN image is 2.5 m per-pixel.

Besides the proposed fusion method (RWPCA_WT), the other three commonly used methods, i.e. such as principal component analysis, discreet wavelet transform based fusion method, optimal filters, and spatial correlation analysis are used for comparison. In RWPCA_WT method, the number of clusters C and the weight control constant λ are set to 30 and 20 respectively.

Figure 1 illustrates the set of source images and fusion results obtained by different fusion methods. As shown in the figure, all fusion methods perform well in the spatial information extraction and injection of the PAN image. However it can be found that the fused images obtained by PCA and spatial correlation analysis have great spectral distortion. The fused images obtained by the wavelet method and spatial correlation analysis methods, especially the ones obtained by the RWPCA_WT fusion methods are with higher spectral preservation.

By a more careful comparison, it can be found that the proposed RWPCA_WT-based fusion method performs better in spatial quality improvement than the spatial correlation analysis based fusion method does. RWPCA-WT method showed superiority over the optimal filter method when an amplitude frequency response of each fused image is obtained by subtracting the amplitude frequency response of each fused MS band obtained by the optimal filter method from that of the corresponding MS band obtained by the RWPCA_WT.

As shown in Figure 1, the fused MS images obtained by the RWPCA_WT-based fused method contain more mid-frequency components than those obtained by the WT-based fusion method. This may be owing to the proposed RW-PCA in the RWPCA_WT fusion method. With the RW-PCA, the spectral information of the original MS image can be well preserved. In addition, more mid-frequency components of the original PAN image can be injected into the fused MS images. Because mid-frequency features are much easier to recognize than high or low frequency features, the fused MS images obtained by the RWPCA_WT method have higher clarity.

When all the visual analysis are put together, it is found that RWPCA_WT method is better in preserving spectral details of original MS image and spatial details of panchromatic images.

In addition, four quantitative metrics employed to evaluate the fusion performance besides the visual analysis, are shown in Table 1 which includes the spectral angular mapper (SAM)[8], the spatial correlation coefficient

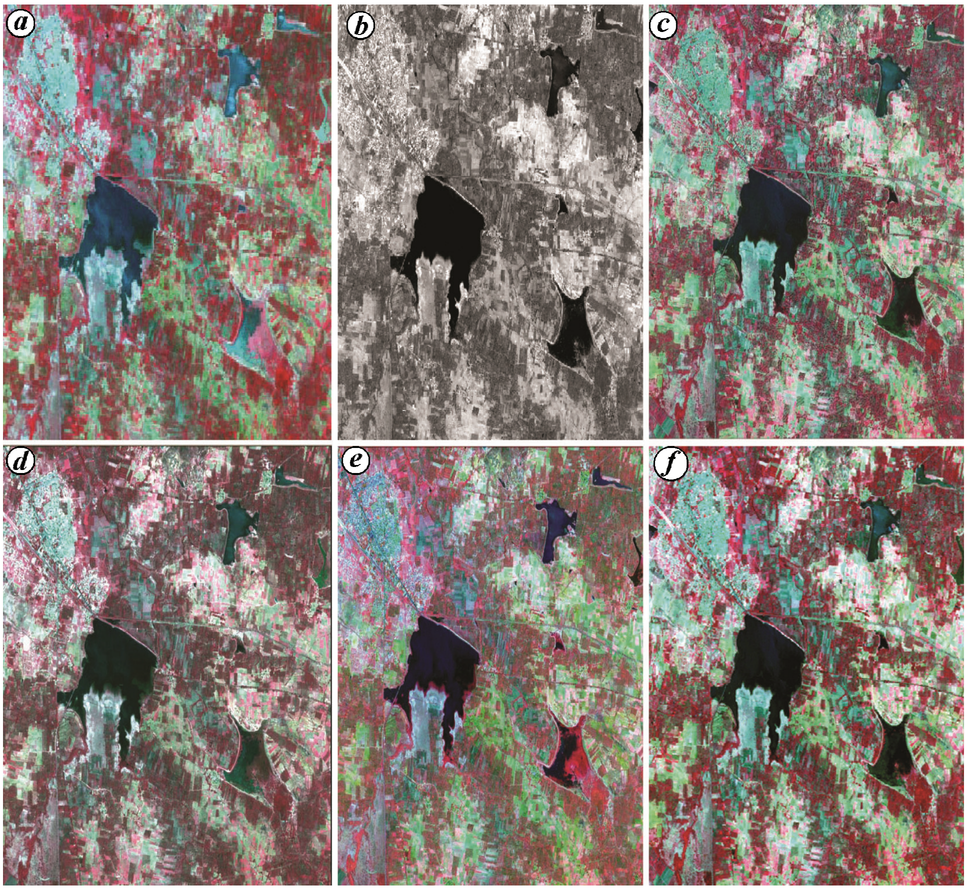

Figure 1. The fusion results of a satellite image. ***a***, Multispectral image; ***b***, Panchromatic image. ***c***, Wavelet method; ***d***, Principal component analysis; ***e***, Spatial correlation analysis; ***f***, RWPCA_WT method.

Table 1. Quantative evaluation results of the remote sensing images

	Evaluation criteria			
Fusion method	SF	SAM	SCC	AG
DWT	0.6 + 0.1	3.0 + 1.9	0.9 + 0.1	14.0 + 6.4
Optimal filters	0.6 + 0.7	3.7 + 2.8	0.9 + 0.1	6.6 + 2.8
Spatial correlation	0.6 + 0.6	2.1 + 1.7	0.9 + 0.1	11.3 + 4
PCA	0.6 + 0.7	2.3 + 1.3	0.9 + 0.2	9.4 + 2.5
RWPCA-DWT	0.7 + 0.6	1.7 + 1.1	0.9 + 0.1	14.3 + 6.8
Reference	1	0	1	+ Infinity

(SCC)[8], the spatial frequency (SF)[9] and the average gradient (AG)[9]. The SAM matrices indicate that RWPCA-DWT fusion method has a high spectral fidelity which is similar to the MS images when compared to other methods. The SCC metric showed that spatial correlation analysis and RWPCA-DWT methods extracted more spatial detail information which has been extracted from PAN image and then injected into the fused MS image. The SF and AG metrics indicated that the clarity of fused MS images is obtained by RWPCA_WT. The larger the values of SF and AG metrics, the higher the visibility of the fused image.

The present study reported a new MS and PAN image fusion algorithm based on the RW-PCA and wavelet. Experimental results demonstrated that the proposed image fusion algorithm performed better in spectral preservation and in terms of other metrics; the proposed fusion method also performed better in spatial quality improvement.

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ACKNOWLEDGEMENT. We thank Dr V. P. Lakshmikanth, Karnataka State Remote Sensing Application Centre (KSRSAC), Bengaluru, for providing the data products for this study.

Received 11 January 2018; revised accepted 13 May 2018

doi: 10.18520/cs/v115/i10/1938-1942

Data visualization by alluvial diagrams for bibliometric reports, systematic reviews and meta-analyses

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Alluvial diagram is a type of flow diagram traditionally used to illustrate the temporal changes in a network composition. However, alluvial diagram can also be utilized as a graphical summary of the demographic data of studies included in a bibliometric report, systematic review or meta-analysis. Such a graphical summary enables readers to quickly discover data patterns and notice the relationships between adjacent data columns. The current study demonstrates such an application of the alluvial diagram and discusses how it facilitates readers to better comprehend the data presented.

Keywords: Alluvial diagram, bibliometrics, meta-analysis, neuroimaging, taste.

SYSTEMATIC reviews and meta-analyses are often considered to be of the highest level of scientific evidence in the hierarchy of academic research[1]. Meanwhile, bibliometric reports allow qualitative and quantitative evaluation of research output on specific topics[2–4] and are now used to evaluate individual researchers and institutions[5,6]. These publications help readers quickly identify and digest the most important and relevant research findings summarized from a vast amount of scientific literature. However, such publications are often long and tedious and the details of the data are usually presented in large tables. Readers may take time to digest the details of information contained in the tables to compare and contrast, and eventually discover data patterns. Meanwhile, alluvial diagram is a type of flow diagram traditionally used to illustrate the temporal changes in a network composition, for example, changes in the structures of scientific disciplines or changes in the usage of words over time[7–9]. However, alluvial diagram can also be utilized as a graphical summary of the background or demographic data of the studies included in bibliometric reports, systematic reviews or meta-analyses. Therefore, this study aims to demonstrate such bibliometric application of the alluvial diagram and discuss how it facilitates readers to better comprehend the data presented.

This study used two examples to illustrate the usefulness of alluvial diagrams in reorganizing and displaying data.

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