

Multispectral and Panchromatic Image Fusion by Combining Spectral PCA and Spatial PCA Methods

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Abstract

An ideal fusion method preserves the spectral information in fused image without spatial distortion. The PCA is believed to be a well-known pan-sharpening approach and being widely used for its efficiency and high spatial resolution. However, it can distort the spectral characteristics of multispectral images. The current paper tries to present a new fusion method based on the same concept. In the conventional standard PCA method, PCA transform is applied to spectral bands of multispectral images, but we applied the PCA transform to pixel blocks instead. Since PCA coefficients are extracted from statistical properties of the image, it is more consistent with type and texture of remotely sensed image compared to other kernels such as wavelets. After that, a new hybrid algorithm is proposed which uses both the spatial PCA and the spectral PCA method to improve the quality of the merged images. Visual and statistical analyses show that the proposed algorithm clearly improves the merging quality in terms of RASE, ERGAS, SAM, correlation coefficient and UIQI; compared to fusion methods such as IHS, Brovey, PCA, HPF, and HPM.

Keywords: Principal Component Analysis (PCA) Transform, Image-Fusion, Multispectral Images, Spatial Information, Spectral Information.

1. Introduction

In remote sensing systems, scenes are observed in different portions of electromagnetic spectrum; therefore, remote sensing images vary in both spectral and spatial resolutions. To collect more photons and maintain signal to noise ratio simultaneously, the multispectral sensors, with high spectral resolution, have a lower spatial resolution compared to panchromatic (PAN) image with a higher spatial resolution, and wide spectral bandwidth. With proper algorithms, it is possible to fuse these images and produce imagery with the best information of both, namely high spatial and high spectral resolution. Prospective

algorithms for the fusion are generally classified into three categories:

- (1) Substitution methods such as IHS and, PCA (Principal Component Analysis) fusion [1],[2].
- (2) Arithmetic combination such as Brovey, SVR (Synthetic Variable Ratio) and RE (Ratio Enhancement) [3].
- (3) Multi-resolution fusion methods, which introduce spatial features from the high-resolution images into the multispectral (MS or color) ones, such as HPF, HPM, RIM, wavelets, Gaussian Laplacian pyramid techniques [4]-[6].

Image-fusion algorithms based on IHS and Brovey distort the spectral information of MS image in the fused result. This distortion of the spectral information during the fusion process is not acceptable in most applications, such as classification procedure [2].

The most commonly used image-fusion methods are those based on the PCA (Spectral PCA and Spatial PCA), but, these can cause spectral or spatial distortion in the results [7].

HPF [8] and HPM [9] fusion algorithms have shown better performance in terms of high-quality synthesis of spectral information. The principle of these methods is to extract the high-frequency information from the PAN image and inject it into the MS image formerly resampled to match the PAN pixel size. Box car filters are used as a low pass filter in these methods. However, the ripple in the frequency response of box car filters has some negative impacts [6].

The multi-resolution fusion techniques such as undecimated wavelets (udW) [10], [11], Non Sub-Sampled Contourlet Transform (NSCT) [12] and Shearlets [13-14] have been discussed widely in recent studies because of their advantages over other fusion techniques. But these techniques are appropriate for cases of image fusion where resolution ratio between the low resolution MS images and the Panchromatic (PAN) image is a power of two [6]. So, an efficient algorithm which

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can fuse the images where the resolution ratio is not the power of two should be developed.

To take advantage of both the spectral PCA technique (which preserves the spatial information) and the spatial PCA technique (which preserves the spectral information), a new hybrid method is proposed in this study which can preserve more spatial and spectral information of initial PAN and MS images.

The paper is structured in six sections. In Section 2, the standard spectral PCA algorithm and its problem for image fusion are being reviewed. Here, a theoretical analysis is done on the amount of spatial information which is preserved by the PCA image fusion method. Section 3 is devoted to the review of the spatial PCA algorithm and its problem. The proposed hybrid model is presented in Section 4. The experimental results and discussions are described in Section 5. Finally, conclusions are given in Section 6. The experimental results show that the proposed algorithm significantly improves the fusion quality in terms of RASE, ERGAS, SAM, correlation coefficient, and UIQI compared to other fusion methods.

2. Standard PCA

PCA is a general statistical technique that transforms multivariate data with correlated variables into one with uncorrelated variables [2], [15]. The coordinates for new axes are computed by an affine transformation of the original data coordinates. It conducts a linear transformation of the multi-spectral space (measure space) into the Eigen vector space (feature space). Let X be an n -dimensional vector, and represent the multi-spectral observation of a pixel of the scene. The principal component transform is defined by:

$$Y = A^T X \quad (1)$$

A is the matrix of normalized Eigen vectors of covariance matrix of X . Then Y has a diagonal covariance matrix:

$$C_y = E\{(Y - m_y)(Y - m_y)^T\} = AC_x A^T = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \lambda_n \end{pmatrix} \quad (2)$$

Where $\lambda_1 > \lambda_2 > \dots > \lambda_n$ are the Eigen values of the covariance matrix of X . The first principal component image PC_1 contains the information that is highly correlated to all MS bands used as input to PCA, while the spectral information unique to any of the bands is mapped into other

components. Then the first principal component PC_1 is replaced by the PAN image, which is first stretched to have the same mean and variance as PC_1 . Finally, performing an inverse PCA transform, given by Equation (3), derives the merged MS images:

$$X = A^{-1}Y \quad (3)$$

The higher the CC (Correlation Coefficient) between fused image and PAN image is, the more similar the two images are, and the more spatial information the fused results have. Here, the performance of PCA method in preserving spatial information is evaluated theoretically. The fused image in the PCA method is:

$$MS_i^h = a_{i1} \times PAN' + a_{i2} \times PC_2 + \dots + a_{in} \times PC_n \quad (4)$$

where PAN' is histogram-matched PAN , n is the number of multispectral band, and a_{ij} coefficients are Eigen vectors in the PCA transform. The histogram matching is such that the mean and standard deviation of PAN image match the mean and standard deviation of PC_1 using the equation [16]:

$$PAN' = PAN \times q + b \quad (5)$$

where $q = \frac{\sigma_{PC_1}}{\sigma_{PAN}}$, $b = m_{PC_1} - q \times m_{PAN}$, σ is the standard deviation, and m is the mean value. The CC between fused image and PAN image is:

$$CC(PAN, MS_i^h) = \frac{E\{(a_{i1} \times PAN' + a_{i2} \times PC_2 + \dots + a_{in} \times PC_n) - \text{mean}(a_{i1} \times PAN' + a_{i2} \times PC_2 + \dots + a_{in} \times PC_n)\}}{\sigma_{MS_i^h}} \times \frac{(PAN - \text{mean}(PAN))}{\sigma_{PAN}} \quad (6)$$

Assuming that PAN image and specific spectral information (PC_2 to PC_n images) are uncorrelated the

$\sigma_{MS_i^h}$ is $\sqrt{a_{i1}^2 \times \lambda_1 + a_{i2}^2 \times \lambda_2 + \dots + a_{in}^2 \times \lambda_n}$ and we have:

$$CC(PAN, MS_i^h) = \frac{E\{(a_{i1} \times PAN' - \text{mean}(a_{i1} \times PAN')) \times (PAN - \text{mean}(PAN))\}}{\sigma_{PAN} \times \sqrt{a_{i1}^2 \times \lambda_1 + a_{i2}^2 \times \lambda_2 + \dots + a_{in}^2 \times \lambda_n}} \quad (7)$$

Substituting Equation (5) into (7), yields:

$$CC(MS_i^h, PAN) = \left(\frac{a_{i1} \times \sqrt{\lambda_1}}{\sqrt{a_{i1}^2 \times \lambda_1 + a_{i2}^2 \times \lambda_2 + \dots + a_{in}^2 \times \lambda_n}} \right) \quad (8)$$

where λ_1 to λ_n are the Eigen values.

Because the value of λ_2 to λ_n is small compared to λ_1 , high spatial information provided by PCA

algorithm can be justified by Equation (8) and (as $\frac{\lambda_2}{\lambda_1}$ to $\frac{\lambda_n}{\lambda_1}$ tends to zero, CC get closer to 1).

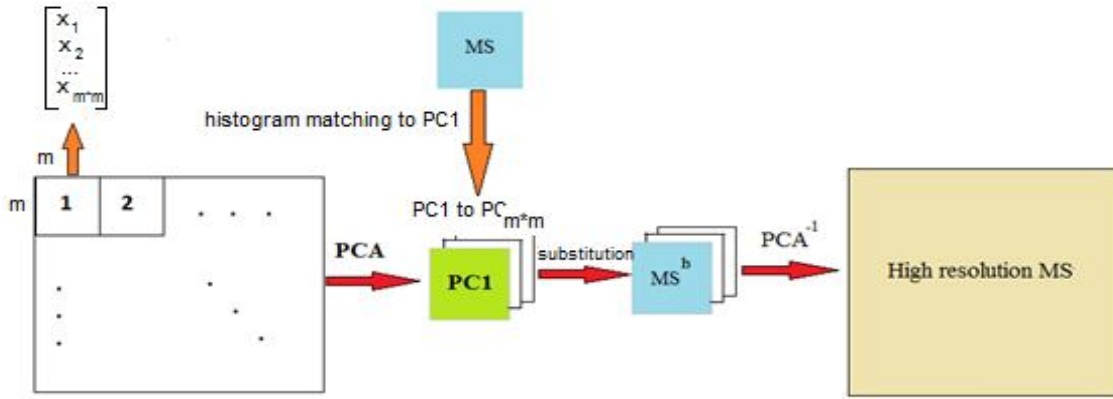


Fig. 1 Application diagram for the fusion of MS and PAN images by Spatial PCA transform.

3. Spatial PCA

Land covers tend to behave in a similar fashion in adjacent bands of the electromagnetic spectrum, so redundant information can be detected in the MS images [2]. In general, the first principal component (PC_1) collects the common information of all bands used as input images in the PCA [2]. This common information can be considered as the spatial information. The fact

To avoid this weak point of the standard PCA, we can apply the PCA transform in spatial domain. The first principal component (PC_1) collects the information that is common to all pixels used as input data in the PCA i.e., the spectral information, while the spatial information that is specific to each pixel is picked up in the other principal components. Fig. 1 shows the general procedure to fuse MS and PAN images, with a spatial resolution ratio of 1: m, based on the spatial PCA. The steps of this method are the following.

1) Split the PAN image up into sub-images at the first step. As shown in Fig. 1, the size of the sub-images should equal the ratio resolution between PAN and MS bands. 2) Place the pixels of each sub-image in a column vector. Apply the PCA transform to these vectors and obtain the principal components. 3) Generate a new MS image whose histogram matches that of the PC_1 image. Note that the size of MS image and PC_1

that pixels are highly correlated with their neighbors also suggests that images contain redundant information. It means that we can split an image up into sub-images and apply PCA to them [17].

As analyzed in Section 2, the PCA method preserves high degree of the spatial information. However implementation results show that the PCA fusion method can lead to a spectral distortion [2].

component is the same. 4) Substitute the PC_1 by the new MS (MS^h) image. 5) Apply inverse PCA transform to new PC components. 6) Do steps 3 to 5 for other MS bands.

There is no need to resample MS images in this algorithm and there is no limitation on the resolution ratio between the low resolution MS images and the PAN image. Similar to Section 2, it can be shown that the preserved spectral information in the spatial PCA method is:

$$CC(MS_i^l, MS_i^h) = \frac{\sum_{j=1}^{m^2} a_{j1} \times \sqrt{\lambda_1}}{\sqrt{\sum_{j=1}^{m^2} a_{j1}^2 \times \lambda_1 + a_{j2}^2 \times \lambda_2 + \dots + a_{jm^2}^2 \times \lambda_{m^2}}} \quad (9)$$

Where MS_i^l is the i th band of multi spectral image, m is the resolution ratio between PAN and MS_i^l , a_{ji} and λ_i denote Eigen vectors and Eigen values in spatial PCA transform respectively. Because the value of λ_2 to λ_{m^2} is small compared to λ_1 , high spectral information provided by PCA

algorithm can be justified by Equation (9) and (as

$\frac{\lambda_2}{\lambda_1}$ to $\frac{\lambda_{m2}}{\lambda_1}$ tends to zero, CC get closer to 1).

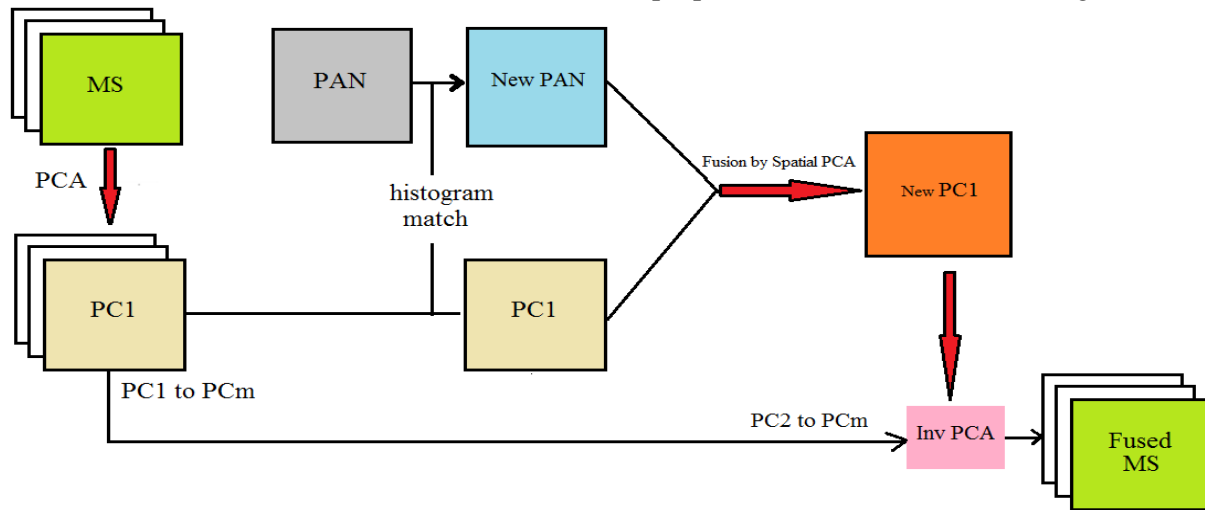


Fig. 2 Proposed hybrid algorithm.

methods based on hybrid concept to integrate the advantages of two fusion methods. Undecimated Wavelet PCA (udWPC) [2], Undecimated Wavelet IHS (udWI) [2], IHS-wavelet [18], IHS-retina-inspired [4], FFT-enhanced IHS [19], and Improved adaptive PCA [20] are the most commonly used hybrid methods. But, because of wavelets or NSCTs which are used in these methods, they can fuse images where the resolution ratio between the low resolution MS images and the Panchromatic (PAN) image is a power of the two [6]. So these are not appropriate for some cases such as LANSAT and SPOT images with resolution ratio 1:3. Some of them use IHS in their fusion methods; however IHS is appropriate where the number of spectral bands is three. So IHS has a limitation too. In Sections 2 and 3, it is shown that PCA and spatial PCA can preserve a high degree of spatial and spectral information respectively. To take advantage of both methods, we can combine spatial and standard PCA. This proposed method has no limitation in image fusion.

Inspired by the PCA-Wavelet model [2], proposed hybrid model is described in Figure. 2 (we use the spatial PCA instead of wavelets in our model). The general procedure for fusion of MS and PAN images, with the spatial resolution ratio of 1: n is as follows: 1) Resample the low-resolution multispectral image to the same size as the high-resolution panchromatic image by the bi-cubic polynomial fit. 2) Apply the PCA transform

4. Proposed Hybrid Method

Over the past few years, several researchers could propose different PAN and MS image-fusion

to MS bands. 3) Generate a new PAN image whose histogram matches that of the PC_1 image. 4) Fuse PC_1 and new PAN by spatial PCA method. The result of this fusion is new PC_1 . 5) Substitute PC_1 by the new PC_1 acquired in step 4. 6) Apply inverse PCA transform to new PC components. This hybrid method can maintain spatial and spectral information simultaneously.

5. Experimental Results and Discussions

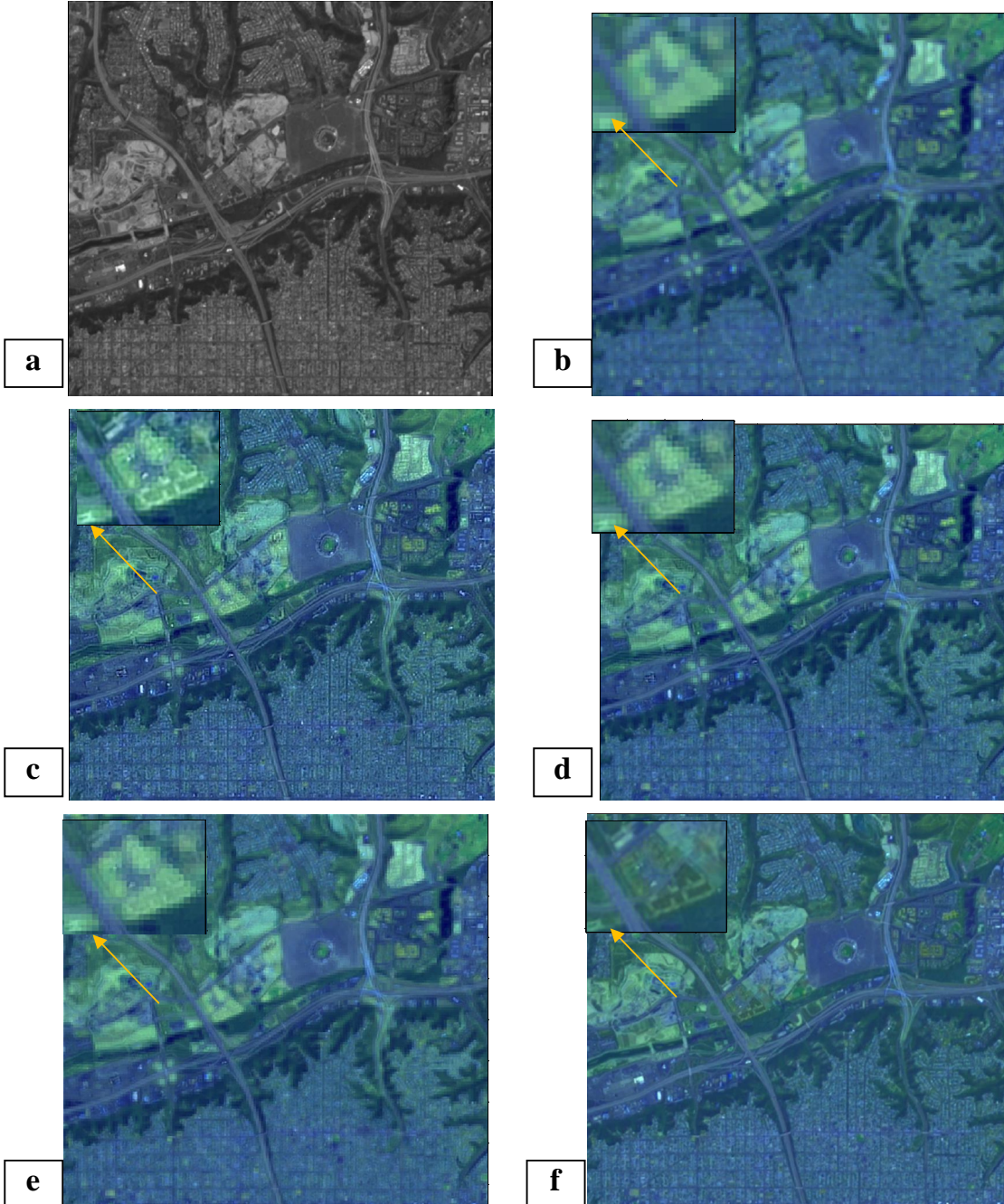
In the current study, SPOT 10-m and LANDSAT (TM) 30-m images were used to evaluate and compare the performance of the following fusion methods:

- Brovey transform, based on the chromaticity transform [15].
- Standard IHS, using the Smith's triangle model [4].
- Standard PCA, using correlation matrix, described in Section 2.
- HPM method which uses box car filters [6].
- Spatial PCA, described in Section 3.
- Proposed Hybrid method, described in Section 4.

Visual comparison of fused images is the first step of quality assessment. The visual performances of the 2, 4, 6 bands of LANDSAT data are shown in Figure. 3. As can be seen in Fig. 3(h), the Brovey has injected a high degree of spatial details of the PAN image, but distortion of the spectral information is not acceptable at all.

The color has been distorted in local and general areas of this image. Because of the bias of the Brovey method [21], general distortion can be justified. As depicted in Fig.3(f) and (g), the spatial details have been pretty good enhanced in the merged image using standard PCA and IHS methods, but some colors have been

predominated on the others in local areas of these images (see magnified area in Fig.3(f) and (g)). By visual comparison, it seems that IHS preserved more spectral information than PCA; however PCA preserved more spatial information than IHS.



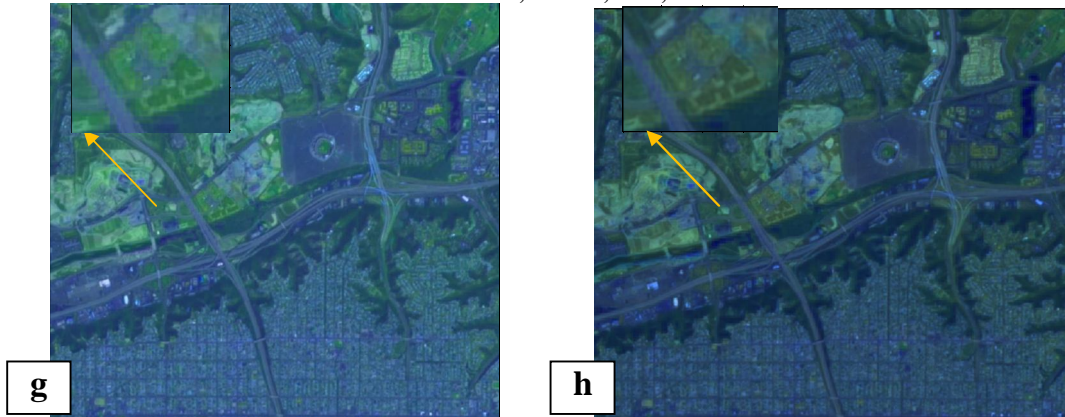


Fig. 3(a) Original PAN. (b) Original MS. (c)Proposed Hybrid method. (d)Spatial-PCA. (e) HPM. (f) PCA. (g) IHS. (h) Brovey.

The result of fusion by HPM method is shown in Fig.3 (e). Filters which are used in HPM method are Boxcar filters and this is the main weak point in the method. This type of filters has long ripple in frequency domain and because of these ripples, fused image seems noisy (see Fig. 3 (e)) [6]. When standard PCA fusion technique is used, the PAN image replaces the PC_1 image, so the whole spatial detail information of this image is present in the resulting fused image [2]. This “too high” spatial information produces solutions that are closer to the SPOT image than desirable and this can lead to spectral distortion in the results [10]. As can be seen from Fig. 3 (d), spatial PCA method preserved the spectral information well, but the edges of the fused image have not been sharpened enough. Because spatial PCA fusion technique replace MS image with the PC_1 image, it maintains the whole spectral information and the fused image is closer to the MS image than desirable. As Fig.3 (c) shows, an image with both high spectral and spatial resolutions is obtained by the proposed hybrid method. In addition to the visual inspection, the performance of each method should be analyzed quantitatively. Since we don't have the reference image (LANDSAT 10 meter) at higher spatial resolution for comparison, the assessment of the selected methods with respect to each other is not easy. Statistical analyses can be performed by two major protocols [22]. In the first protocol, analyses are carried out at the full spatial resolution without any degradation. But in the second, original PAN and MS images are spatially degraded down to a lower resolution in

order to compare, merged result with the genuine references resolution. In the second protocol, we degrade images, such that the resolution of PAN image is degraded to 30 meter, and the resolution of MS images is degraded to 90 meter. After fusion, we obtain MS with resolution of 30 meter and now we can compare this fused MS image (30 meter), with initial MS image (30 meter).

A. Assessment by First Protocol

Recently proposed by Alparone et al. [22], the QNR index evaluates the quality of the fused image without requiring the reference MS image and combines the two distortion indexes of the spectral and spatial distortion. The spectral distortion index (D_λ) is calculated as:

$$D_\lambda = \sqrt{\frac{1}{N(N-1)} \sum_{t=1}^N \sum_{r=1, r \neq t}^N |Q(MS_t, MS_r) - Q(F_t, F_r)|} \quad (10)$$

Where MS represents the initial MS bands, F is the fused image, N is the number of MS bands, and Q denotes the universal image-quality index calculation [22]. If the MS and fused images are identical, these metrics have zero value. The spatial distortion index (D_s) is computed as:

$$D_s = \sqrt{\frac{1}{N} \sum_{t=1}^N |Q(F_t, P) - Q(MS_t, \tilde{P})|} \quad (11)$$

Where P and \tilde{P} denotes the PAN image and the low-pass filtered PAN image respectively [22]. \tilde{P} is obtained by filtering of the PAN such that resolution of \tilde{P} and MS is equal (note that resolution of fused image (F) and PAN image (P) is equal also). Finally the QNR index is defined as:

$$QNR = (1 - D_\lambda)(1 - D_s) \tag{12}$$

When the radiometric (spectral) and geometric (spatial) distortions are both zero, the QNR value will be maximal and equals 1. Table I shows the performance comparisons of the fused images by QNR index. D_λ is the spectral index and the low value of the D_λ shows that spectral information is preserved very good. The low value of D_s shows that high degree of spatial information is injected into the MS bands. The QNR is the combination of D_λ and D_s and determines the spectral and spatial information of the fused image simultaneously (the best value of QNR is 1). The results of this table show that an image with simultaneous high spectral and spatial resolution can be achieved by the proposed Hybrid method. In Sections 2 and 3, we have extracted an

equation which shows the value of spatial and spectral CC of PCA and spatial PCA. Table II shows the real CC value and extracted equation value. As can be seen from this table, extracted equations are valid.

B. Assessment by Second Protocol

Quantitative analysis can be done at the inferior level too. As explained before, MS and PAN image are degraded and initial MS image can be used as reference image.

Table1: Assessment by the first protocol

	HIS	PCA	Brovvey	HPM	Spatial PCA	Proposed Hybrid Method
D_λ	0.018	0.048	0.076	0.063	0.035	0.001
D_s	0.225	0.240	0.244	0.063	0.052	0.037
QNR	0.760	0.723	0.697	0.876	0.914	0.962

Table 2 Assessment of PCA and spatial PCA algorithm by CC metric.

	$CC(MS_i^h, PAN)$	Equation (8)	$CC(MS_i^h, MS_i^s)$	Equation (9)
PCA	0.98	0.98	----	----
Spatial PCA	----	----	0.86	0.84

Table 2 Assessment by the second protocol

	HIS	PCA	Brovvey	HPM	Spatial PCA	Proposed Hybrid Method
CC	0.764	0.759	0.773	0.804	0.765	0.817
ERGAS	5.22	5.18	6.87	4.84	5.54	4.52
RASE	1.46	1.52	2.32	1.59	1.62	1.38
Q4	0.756	0.752	0.750	0.791	0.760	0.817
SAM	0.04	0.04	0.03	0.05	0.06	0.03

Degraded version of the MS and PAN images are used in the image fusion procedure and the fusion result should be compared with initial MS image. In order to assess the quality of the merged images at the inferior level, five objective indicators were used:

- 1) Correlation Coefficient

It is defined as [10], and indicates the degree of linear dependence between the original reference and fused images. If two images are identical, the correlation coefficient is maximal and equals 1.

- 2) RASE

This percentage [12] characterizes the average performance of the image fusion method in the considered spectral bands:

$$RASE = \frac{1}{M} \sqrt{\frac{1}{N} \sum_{i=1}^N RMSE^2(F_i, R_i)} \quad (13)$$

Where M is the mean radiance of the N spectral bands of the original MS bands (reference image), RMSE is the root mean square error and R is the reference image.

3) ERGAS

ERGAS (or relative global dimensional synthesis error) is as follows [2]

$$ERGAS = 100 \frac{h}{l} \sqrt{\frac{1}{N} \sum_{i=1}^N \frac{RMSE^2(F_i, R_i)}{M_i^2}} \quad (14)$$

Where h is the resolution of the high spatial resolution image, l is the resolution of the low spatial resolution image, and M_i is the mean radiance of a specific band involved in the fusion.

The lower the value of the RASE and ERGAS, the higher the quality of the merged images.

4) SA or SAM

The spectral angle mapper (SA or SAM) between each band of the original reference multispectral and the fused image is calculated as follow [20]:

$$SAM(u, \hat{u}) = \arccos\left(\frac{\langle u, \hat{u} \rangle}{\|u\|_2 \|\hat{u}\|_2}\right) \quad (15)$$

Where $u = \{F_1, F_2, \dots, F_N\}$ is the original reference spectral pixel vector, and $\hat{u} = \{R_1, R_2, \dots, R_N\}$ is the spectral pixel vector of the fused image. SAM is calculated in degrees for each pixel vector, and it is averaged on all pixels to obtain a single value. It should be as close to 0 as possible.

5) Q4 Index

It is defined as follows [23]:

$$Q = \frac{\sigma_{FR}}{\sigma_R \sigma_F} \frac{2m_R m_F}{m_R^2 + m_F^2} \frac{2\sigma_R \sigma_F}{\sigma_R^2 + \sigma_F^2} \quad (16)$$

Where F and R, m , σ are fused, reference images, mean of image and standard deviation of image respectively. The universal image quality index (UIQI or Q4) models any distortion as a combination of three different factors: loss of linear correlation, contrast distortion and luminance distortion. The Table III shows the values of these quality metrics for proposed methods and other mentioned methods. As can be seen from Table III, the quality indexes obtained by applying proposed methods are all pretty good compared with those obtained by applying other methods.

6. Conclusion

A new pan-sharpening method based on the PCA transform is proposed in this paper. In conventional standard PCA method, the PCA transform is applied to the spectral bands of MS images. The result and theoretical analysis showed that, the PCA method preserved spatial information well, however PCA led to the spectral distortion. In order to use the PCA transform potency, we applied the PCA transform in the spatial domain. Result and theoretical analysis showed that this method can preserve more spectral characteristic. To take advantage of both methods, a new hybrid method was proposed in this paper which can preserve more spectral and spatial information simultaneously. Finally, the fusion results of the proposed method were compared to the results of some well-known methods at high and inferior levels. The visual results showed that the hybrid method can achieve better performance. In addition to the visual inspection, the performance of each method was analyzed quantitatively. The statistical analyses tools such as RASE, ERGAS, SAM, the correlation coefficient and Q4 was demonstrated that the proposed algorithm increased spectral and spatial information contents and reduced the color distortion compared to the counterpart fusion methods.

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