



Multi-spectral remote sensing image enhancement method based on PCA and IHS transformations

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Received June 14, 2010; Revision accepted Jan. 10, 2011; Crosschecked May 24, 2011

Abstract: This paper introduces a new enhancement method for multi-spectral satellite remote sensing imagery, based on principal component analysis (PCA) and intensity-hue-saturation (IHS) transformations. The PCA and the IHS transformations are used to separate the spatial information of the multi-spectral image into the first principal component and the intensity component, respectively. The enhanced image is obtained by replacing the intensity component of the IHS transformation with the first principal component of the PCA transformation, and undertaking the inverse IHS transformation. The objective of the proposed method is to make greater use of the spatial and spectral information contained in the original multi-spectral image. On the basis of the visual and statistical analysis results of the experimental study, we can conclude that the proposed method is an ideal new way for multi-spectral image quality enhancement with little color distortion. It has potential advantages in image mapping optimization, object recognition, and weak information sharpening.

Key words: Remote sensing, Principal component analysis (PCA), Intensity-hue-saturation (IHS) transformation, Image enhancement, Spatial information, Spectral information

doi:10.1631/jzus.A1000282

Document code: A

CLC number: TP7

1 Introduction

Since the launch of the first satellite sensors in the 1970s, remote sensing images have been widely used in basic surveying and mapping (Swaminathan *et al.*, 1983; Suga, 1992; Smith and Wyatt, 2007), geology detection (Cengiz *et al.*, 2005; Bedini, 2010), and land resources monitoring (Mas, 2004; Lu *et al.*, 2006), etc. All the applications required support of remote sensing image enhancement methods. For basic surveying and mapping, false color composition and image fusion are commonly used methods (Chiuderi, 1997; Zhang *et al.*, 2007). Lithology, alteration mineral, heavy oil, and geothermal resources

have faint signals compared to other earth surface objects. In order to detect such information with remote sensing techniques, image enhancement is needed (Ramadan and Kontny, 2004; Ninomiya *et al.*, 2005; Kratt *et al.*, 2006; Zhang *et al.*, 2009). For land resources monitoring, as for land use investigation and dynamic monitoring, multi-spatial, multi-temporal, and multi-spectral remote sensing image fusion is required (Wilkinson *et al.*, 1995; Simone *et al.*, 2002; Shimoni *et al.*, 2009).

Data fusion is the most commonly used remote sensing image processing method. It is a formal framework in which are expressed methods and tools for the fusion of data originating from different sources. It aims at obtaining information of greater quality (Wald, 1999). It is an important tool for information enhancement, spatial resolution improvement, multi-data integration, and change detection

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(Pohl and Genderen, 1998). Many fusion methods have been developed in the past, such as the intensity-hue-saturation (IHS), principal component analysis (PCA), high pass filter (HPF), Brovey transformation (BT), and wavelet transformation (WT). They were applied to various types of data sets, including single sensor multi-temporal images (Weydahl, 1993), multi-sensor multi-temporal images (Pohl and Genderen, 1995), single sensor multi-spatial resolution images (Wald *et al.*, 1997), multi-sensor multi-spatial resolution images (Welch and Ehlers, 1987; Chavez *et al.*, 1991), and remote sensing images with ancillary data (Janssen *et al.*, 1990).

In the past, most attention was paid to image enhancement with different remote sensing images (Pohl and Genderen, 1998; Simone *et al.*, 2002). The spatial and spectral information of the widely used multi-spectral images as Landsat series sensor images were not efficiently used. Their spatial resolution is lower than most of the commonly used high spatial resolution images, such as SPOT, IKONOS, and Quick Bird. Neither their roles nor functions can be substituted in the character of multi-spectral, low price, large coverage, and historical data trace. With such images, especially for image interpretation or classification, it would be much better to use all the information contained in the original data, rather than obtain optimum image display with other expensive high spatial resolution images. However, there is still no applicable method to enhance the spatial information in these images, without losing their spectral resolution.

PCA and IHS transformations are useful image processing techniques that have been commonly applied during the last two or three decades. They are very simple and easy to use, and were introduced in most of the image processing commercial software (Tu *et al.*, 2001; Wu *et al.*, 2003; He *et al.*, 2004).

PCA is a statistical technique that is useful for image encoding, image data compression, image enhancement, digital change detection, multi-temporal dimensionality, and image fusion (Pohl and Genderen, 1998). When used in image fusion there are two approaches. PCA of the multi-channel image replaces the first principal component by other images, which is a commonly used approach and often uses high spatial resolution images to replace the first component. Thus it can increase the spatial resolution of a multi-channel image (Chavez *et al.*, 1991). The

other approach is PCA of all the multi-image data channels. This approach combines image data from different sensors into one multi-band image, and then performs PCA on all bands of this image (Yésou *et al.*, 1993; Rokhmatuloh *et al.*, 2003).

The IHS technique is a standard procedure in image analysis. It serves feature enhancement, the improvement of spatial resolution (Canisius and Turrall, 2003), the fusion of disparate data sets (Chen *et al.*, 2003), and color enhancement of highly correlated data (Gillespie *et al.*, 1986), etc. The use of the IHS technique in image fusion is manifold, but based on one principle that is to replace one of the three components (intensity (I), hue (H), and saturation (S)) of one data set with another image. Most commonly, the intensity channel is substituted (Pohl and Genderen, 1998). Until now, the study of improvement on the IHS method has been focused on the pre-processing of the three components (I, H, or S) or high spatial resolution images before the fusion procedure (González-Audícana *et al.*, 2004; Zhang and Hong, 2005; González-Audícana *et al.*, 2006).

In order to find a way of enhancing the images from single sensor multi-spectral and single temporal images without other ancillary images or data, this paper proposes a fusion method based on PCA and IHS transformations. It is hoped that this method could be used in image mapping optimization, object recognition, and weak information sharpening in the future.

2 Methods

The proposed method is based on two principles: (1) Both PCA and IHS mergers can separate most of the spatial information (intensity) of a multi-spectral image or a selected band combination from its spectral information by means of linear transformation. The PCA separates the spatial information of the multi-spectral image into the first principal component, and the IHS transformation separates the spatial information of the selected band combination of the multi-spectral image as the intensity components (González-Audícana *et al.*, 2004). (2) The spatial information contained in the first principal component of the PCA is richer than the intensity component of the IHS transformation.

The main process of the method is achieving the intensity bands by performing PCA and IHS transformations on the original multi-spectral image, then replacing the intensity component of IHS transformation by the first components of PCA, and finally obtaining a new image with abundant information, less redundancy by performing inverse IHS transformation. Following are the detailed steps of the method (Fig. 1):

1. Transform the original multi-spectral image into the PCA components: PC1, PC2, ..., PC n , perform IHS transformation in a combination of three selected bands of the original multi-spectral image, and obtain three new components: I, H, and S.

2. Matching the histogram of the first principal component (PC1) to that of the I component of the IHS transformation.

3. Substitute the I component of the IHS transformation by the principal component that has been matched to the intensity component, as a new intensity component (I').

4. Perform inverse IHS transformation on the new I', H, and S components, and obtain a new RGB image.

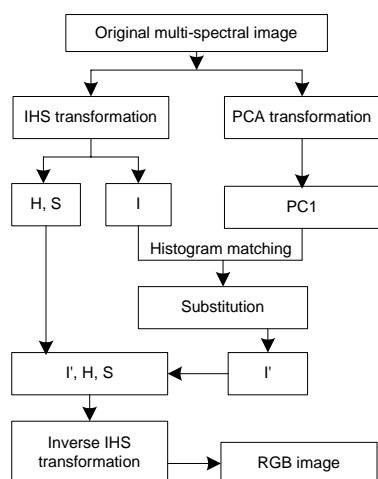


Fig. 1 Flowchart of the proposed fusion method

3 Experimental study

To test the validity of this method, a Landsat 7 ETM+ subscene of Ningbo in Zhejiang Province, China (Path 118/Row 39), acquired on 13 March 2001, was selected as the experimental data. It is an area with complicated and typical land cover types

such as road, urban, plantation, mountain, tideland, island, seashore pond, seashore polder, sea, and aqueduct (Fig. 2a). The image was radiometrically and geometrically corrected and transformed to Transverse Mercator, and the geographic datum is WGS-84. All bands except bands 6 and 8 were chosen as the test bands. Then, all the six multi-spectral bands are used as PCA input data. Since there are 120 (P_6^3) false color combinations in all, in this study, only three commonly used combinations of bands 7-4-3, 5-3-2, and 3-2-1 were chosen as IHS transformation input bands.

By performing PCA on the original multi-spectral image, six uncorrelated bands were obtained. The first component represents the integrated intensity information of all the original bands, and other components mainly represent some specific information such as soil, vegetation, wetness, and mineral, or noise information. After replacing the intensity component of all three chosen IHS transformation results by the first principal component, three useful fused RGB images were created by performing inverse IHS transformation (Fig. 2).

Generally, image assessment methods can be divided into two classes: qualitative (or subjective) methods and quantitative (or objective) methods (Shi *et al.*, 2005). In this study, visual analysis was used as the qualitative method, and statistical analysis was used as the quantitative method.

3.1 Visual analysis

Visual analysis is a commonly used quality assessment method for image processing. The principle is to put different output images and the original image together, compare the definition, contrast ratio, and detail texture of each image, and then give a reasonable judgment by visual interpretation. Most of the studies used image plates to compare the results (Oguro *et al.*, 2003; Nikolakopoulos, 2004). Furthermore, some studies invited experts to make assessments (Laporterie-Déjean *et al.*, 2005; Acerbi-Junior *et al.*, 2006). In this study, image plate comparison was employed.

As shown in Fig. 2, the first grayscale principal components of PCA have abundant integrated intensity information (Fig. 2a). However, it is difficult to distinguish detailed information amongst different objects by visual interpretation on this grayscale,

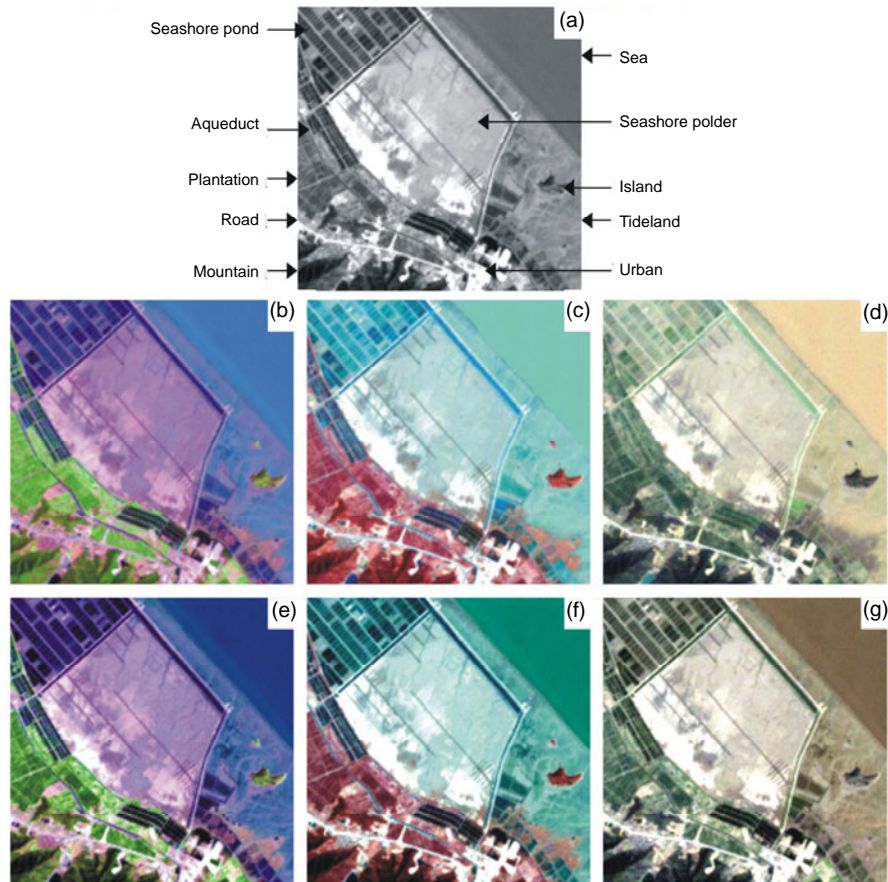


Fig. 2 Original grayscale images of PCA, the original ETM+ false color RGB images, and the results of the proposed fusion method

(a) First principal component of PCA; (b)–(d) False color RGB image of ETM+ bands 7-4-3 (5-3-2, or 3-2-1); (e)–(g) Fused results generated by the ETM+ bands 7-4-3 (5-3-2, or 3-2-1) with the first principal component of PCA

image. The fusion results (Figs. 2e–2g) are rich in color and they are clearer and more vivid with good texture features than the original false color images (Figs. 2b–2d). For example, the textures of plantation, seashore polder, tideland, road, and urban area on Fig. 2e are much clearer than those of the original RGB image (Fig. 2b). With those enhanced images, the boundaries of different land surface objects are more easily identified.

3.2 Statistical analysis

Statistical analysis is a numerical value operation method. It uses some parameters that can reflect the spatial and the spectral information to assess the image quality. The correlation coefficient, mean value, standard deviation, and variance are statistical parameters that are most commonly used (Oguro *et*

al., 2003; Rokhmatuloh *et al.*, 2003; Garzelli and Nencini, 2005; Acerbi-Junior *et al.*, 2006). Information entropy and warping degree are the next commonly used parameters (Armenakis *et al.*, 2003; Shi *et al.*, 2005). Furthermore, there are some other parameters such as ERGAS, SQ, Q, and Q4 (Alparone *et al.*, 2004; Nencini *et al.*, 2007). In this study, the mean value, standard deviation, information entropy, and correlation coefficient were chosen as assessment parameters. The mean value represents the mean intensity of the image; the standard deviation represents discrete degree between each pixel and the mean value of one image; the information entropy measures the richness of information of an image; the correlation coefficient represents the similar degree between the original image and the fusion image. The formulas of these parameters are all referenced by Shi *et al.* (2005).

Tables 1, 2, and 3 show that the mean value and the standard deviations of all the fused image bands are much larger than those of the original RGB bands. Under the condition which prohibits histogram changes on the fused images and original images, the enlarged mean value and the standard deviation could be attributed to the imported PC1 of PCA. Furthermore, the changed standard deviation indicates that the spectral resolution of the fused image bands is much wider than that of the original image bands.

For the information entropy, different band combinations have different characteristics. In Table 1, the information entropies of the fused band R and band B increased whilst that of band G decreased. In Table 2, the information entropies of the fused band R and band G increased whilst that of band B decreased. In Table 3, the information entropy of the fused band R increased whilst those of band G and

band B decreased. Those features are the basis for using the three fused images to identify different objects. For example, the boundary of plantation in Fig. 2e is clearer than that of Fig. 2b, due to the decreased information entropy of band G. The boundary of seashore pond in Fig. 2f is clearer than that of Fig. 2c, due to the decreased information entropy of band B. The boundary of tideland in Fig. 2g is clearer than that of Fig. 2d, due to the decreased information entropies of band G and band B.

The correlation between the original band and the fused band ranges from 0.75 to 0.96 (Tables 1, 2, and 3). It indicates that the first principal component of the PCA introduces most of the original multi-spectral image information into the fused image. This means that the color distortion introduced by the proposed method is relatively low, which is also shown in Fig. 2.

Table 1 Statistical parameters of the original ETM+ false color image bands of 7-4-3 and the fused image bands

Image	Band	Mean	Standard deviation	Information entropy	Correlation coefficient
Original multi-spectral image (ETM+ 7-4-3)	Band 7	48.51	19.69	15.74	
	Band 4	50.23	12.35	31.60	
	Band 3	68.13	16.80	21.37	
Fusion image (ETM+ 7-4-3,PC1)	R	111.95	70.26	32.88	0.96
	G	104.81	51.62	27.01	0.84
	B	99.76	61.23	29.86	0.85

Table 2 Statistical parameters of the original ETM+ false color image bands of 5-3-2 and the fused image bands

Image	Band	Mean	Standard deviation	Information entropy	Correlation coefficient
Original multi-spectral image (ETM+ 5-3-2)	Band 5	65.43	23.81	13.37	
	Band 3	68.13	16.80	21.37	
	Band 2	68.79	10.75	41.47	
Fusion image (ETM+ 5-3-2,PC1)	R	120.28	68.55	28.73	0.93
	G	95.28	60.00	27.45	0.87
	B	102.53	61.10	28.52	0.87

Table 3 Statistical parameters of the original ETM+ false color image bands of 3-2-1 and the fused image bands

Image	Band	Mean	Standard deviation	Information entropy	Correlation coefficient
Original multi-spectral image (ETM+ 3-2-1)	Band 3	68.13	16.80	21.37	
	Band 2	68.79	10.75	41.47	
	Band 1	86.60	8.62	49.71	
Fusion image (ETM+ 3-2-1,PC1)	R	118.70	59.99	32.45	0.76
	G	128.95	60.76	32.09	0.75
	B	118.94	57.39	31.11	0.78

4 Discussion and conclusions

This study introduced a new fusion method for single sensor and single temporal multi-spectral image enhancement, and assessed the quality of the resulting synthetic images by visual interpretation and statistical analysis. The method presented in this work differs from all the other commonly used fusion methods. The objective is not to enhance the spatial resolution of the original image, but to make full use of the intensity information and to retain the spectral information that is contained in the original multi-spectral image.

To increase information content for visual interpretation from multi-spectral images, the traditional false color RGB image bands are often modified. Commonly employed alternatives include: (1) adding different single bands together to obtain a new integrative band, and using it as a false color band; (2) making use of the IHS color transformation; (3) applying PCA to the original image. However, the three methods have their own shortcomings. The first method will result in redundant information and color distortion in the output image. The output image from three bands of the IHS transformation will lose much of the information of the original image. Since the output data is uncorrelated, the principal components of PCA can produce more colorful color composite images than spectral color composite images, but the false color image of the principal components often causes large color distortion. The proposed method imported almost all the intensity information into the fused images by replacing the intensity component of the IHS transformation with the first principal component of the PCA transformation. It made full use of the merits of the PCA and IHS transformations and avoided their shortcomings. It could be a very good tool for multi-spectral image enhancement. The experimental results indicated that the fused images retained most of the spatial and the spectral informations of the original multi-spectral image. The fused images are better than the original false color images with vivid color and clear texture.

For all the remote sensing images with medium spatial resolution but high spectral resolution like Landsat TM/ETM+, Terra ASTER, and HJ-1A/B, the key problem is not enhancing the spatial resolution but making use of the abundant spectral information.

In this study, only the first principal component of the PCA was used to enhance the integrated intensity information. In fact, other components that represent some special objects, such as soil, water, vegetation, and mineral, can also be used as the role of the first principal component. They could introduce special spectral information into the fused image and could help to identify special objects in an image. Thus for those using the multi-spectral remote sensing image for environmental evolution analysis, resource investigation, and image interpretation or classification in the future, the proposed method could be an optimal information analysis and enhancement tool.

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