Pan-Sharpening Landsat Images through the Component Substitution Methods

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Abstract

Remotely sensed images have played a valuable role in several applications such as image classification, feature extraction, land cover monitoring, and others; thus, the need for high-resolution satellite images has become necessary and essential. In order to produce images with very high spectral and spatial resolution, the pan-sharpening techniques—, which are regarded as a subset of data fusion techniques—combine the color information of the multispectral image from the same scene with the distinct geometric features of the panchromatic image. This work conducts a comparative analysis of four pansharpening methods (Gram, HIS, Brovey, and PC) specifically applied to Landsat 7 images, providing a thorough evaluation across multiple performance metrics. Also we introduce and apply performance metrics that not only measure quantitative accuracy (like RMSE and RASE) but also assess the preservation of spatial details, offering a more holistic evaluation of pansharpening techniques. The qualitative and quantitative results indicate that both GS and IHS techniques have accurate performance.

Keywords: Pansharpening; Component substitution; Principal Component Analysis; Gram-Schmidt; Brovey; HIS; Landsat 7 images

1. Introduction

In an era where data-driven decisions shape our understanding of the world, the role of remote sensing has attained unprecedented importance. The applications of remote sensing span a diverse array of fields, from resource exploration and environmental monitoring to disaster management and urban planning. Each one of these applications request high-quality images that can deliver together spatial detail and spectral richness, essential for accurate analysis and interpretation [1,2,3].

Most Earth observation satellites produce voluminous data in multiple spectral bands, each with varying spatial resolutions due to constraints in storage and transmission bandwidth. The quality of the satellite images is intrinsically linked to these resolutions: spatial resolution shows the smallest feature that can be represented by a pixel in a satellite image, while spectral resolution indicates the capacity of satellite sensors to estimate certain wavelengths from the electromagnetic spectrum. So, the high spectral resolution of the satellite means the ability to capture hundreds of bands with similar spatial area, but at the same time, the narrow wavelength for each band [2,4].

Numerous Panchromatic (PAN) and multispectral (MS) satellite images are obtained by Earth observation remote sensing platforms. The MS images have high spectral resolution with color information that helps to distinguish between different areas of the captured images that used in diverse remote sensing applications, while PAN images involve one band only with high spatial resolution, but it lacks spectral resolution (imprecise color data) and does not have any color information [5,6].

Therefore, it is feasible to combine the MS color information and clear geometric features of PAN image to produce new MS image with higher spatial resolution by performing appropriate algorithms. This process, called

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pan-sharpening method, aims to construct synthesized MS images with high spectral and spatial resolution content extracted from both MS and PAN input images [4,7,8].

The pansharpening methods aims to incorporate the clear geometric features from a higher spatial resolution (fine) panchromatic image , and color information from coarse multispectral image to produce sharpen MS spatial resolution images, Consequently, the enhanced image shows PAN image with a high spatial resolution and MS image with a high spectral resolution [9,10].

In the literature, numerous techniques of pan-sharpening have been presented. Generally, these techniques are classified into three main categories, which are Component Substitution (CS), Multi-Resolution Analysis (MRA), and Variational Optimization (VO) techniques [11].

The main category is the CS group. It is often denoted as a spectral class where suitable transformations have been performed on MS image to separate the spatial and spectral components. Next, the histogram of PAN image is adjusted to match the histogram of MS spatial component. After that, PAN image is substituted for the spatial component of the MS image. Finally, the inverse transformation is derived in order to transfer the altered components to the MS image space [12].

In the Multi-Resolution Analysis (MRA) group, called spatial class, the pyramid or wavelet transformation functions is used to decompose both MS and PAN images into scale levels. In a one decomposed level, the spatial information is extracted from a PAN image and insert into corresponding scale level of the decomposed MS image. Ultimately, the inverse decomposition process is utilized to produce the pansharpening [5].

In Variational Optimization (VO) based technique, a priori knowledge of the scene or sensor such as statistical properties are used to model the target energy function, which quantifies the "quality" of an enhanced image, and then the optimization algorithms are used to minimize (or maximize) the target energy function to find the best solution for the enhanced image [13].

This paper presents four techniques belong to component substitution (CS) approach pan-sharpening to enhance Landsat7 satellite images through two case studies. The layout of the paper is as follow: a brief explanation of the techniques employed is presented in section 2 and section 3 presents the study areas and experimental results, followed by conclusions in section 4.

2. Pan-Sharpening Methods

Four CS pansharpening methods have been adopted to enhance the Landsat7 ETM+ images selected in Iraq. Both MS and PAN scenes derived from the same satellite are used to perform Principal Component Analysis (PCA), GramSchmidt (GS), IHS, and Brovey pansharpening methods.

2.1. Principal Component Analysis (PCA)

PCA is a powerful statistical technique broadly applied in satellite image processing. It utilizes to enhance image data, dimensionality and noise reduction and improve interpretability while preserving important and crucial information [14].

The steps for implementing PCA are as follows:

1- Apply a linear transformation on MS image to create a collection of scalar images that denotes as (principal components).
2- The first principle component contains the majority of the spatial information, whereas the spectral information in remaining principal components.
3- Histogram matching is performed to align the intensity range of PAN image with the first principal component of MS image.
4- Replace the first principal component with spatial information derived from the PAN high-resolution image.
5- The first primary component of the PAN image conducts histogram matching in order to decrease distortion in the PCA pansharpening method.
6- Implement the inverse linear transform to obtain the final improved images [9,15,16].

2.2. GramSchmidt (GS) Method

The Gram-Schmidt (GS) spectral sharpening method is a notable pan-sharpening technique that was introduced by Laben and Brover in 1998 and later patented by Eastman Kodak (Laben and Brover, 2000). It is based on a mathematical approach that involves the orthonormalization of a set of vectors. In image processing context, every the (PAN) and (MS) images relates to one vector [8]. This method based on component substitution scheme and broadly used by implementing the following steps:

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1- Simulating a panchromatic band (B_{sim}) from the multispectral (MS) image using the following equation:

$$B_{sim} = \sum_{k=1}^{n} W_k MS_k \qquad (1)$$

W_k is the pixel's weight, and MS_k is the multi-spectral image. The first band of the Gram-Schmidt transformation is represented by the simulated lower spatial resolution Pan image (B_{sim}).

2-The GS transformation has been executed on the simulated PAN band with the other lower spatial resolution spectral bands.
3-The high spatial resolution PAN image and the first from the Gram transform band generated -Schmidt are statistically adjusted to provide an improved higher spatial resolution PAN image.
4-An improved higher spatial resolution PAN image is used in place of the first transform band from the GS to produce a new set of transformed bands.
5-Eventually, new set of transform bands then goes through to the inverse GS transformation to produce the enhanced spatial resolution MS image [17, 18, 19, 20].

2.3. Brovey Transform Method

An arithmetic-based pansharpening technique called the Brovey transform (BT) was developed using the mathematical combination of the MS and Pan picture. The transformation was created to enhance the contrast between an image histogram's low and high ends in order to create visually appealing images [21].

Each MS image will be normalized upon the other spectral bands then multiplication with PAN one to append the spatial information to the output result. Mathematical formula shows the Brovey transform is [22,23]:-

$$E_i = \frac{PAN}{\frac{1}{N}\sum_{i=1}^{N} MS_i} MS_i \qquad (2)$$

2.4. Histogram-Matched IHS Method

The popular pan-sharpening technique is characterized by its fast and quick process and can be applied to large volumes of data to obtain improved images. The basic steps of IHS method can be abstract as the following:

1- The MS images are converted from RGB to IHS (Intensity, Hue, and saturation) color space by implementing IHS transform.
2- Perform histogram matching between PAN and the intensity images (I) to adjust PAN image intensity distribution to match the statistical properties of the Intensity component of MS image.
3- The adjusted histogram matches PAN image and replaces the intensity image (I).
4- Implement inverse IHS transform to produce the final pansharpening image [3,23,24].

3. Study Area and Experimental Results

In this work, the recent Landsat 7 ETM+ images collected using the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Data Center via the Global Visualization Viewer (Glovis) (http://glovis.usgs.gov/) or Earth explorer (http://earthexplorer.usgs.gov/) web interface are used as applicable dataset. The selected study area covered WRS-2 path 168 and row 36 and 37 that covers an area in Iraq. The three true color bands (band1, band2, and band3) are used as MS images, and the panchromatic band (band 8) is used as PAN images. Two case studies have been selected from the study area to create an accurate statistical investigation on the assessment of the pan-sharpening techniques and to establish generalization conclusions where the pansharpening techniques are tested on sampled from various scenes, such as urban agricultural and water-covered areas. Each sample image with a size 400x400 has been processed with the pansharpening methods.
Figure 1 (a and b) presents the PAN and MS images for both the first and second case study where the full-resolution PAN image and the original true color MS image, expanded to the scale of PAN are presented for case studies 1 and 2. The first one shows an agricultural area consisting of fields represented as rectangular plots with varying shades indicating different crops or stages of growth. Also, the area in the lower left corner includes a meandering river surrounded by vegetation patches. The second case study consists of a combination of urban and rural area. In addition, there is a network of roads surrounding urban area and a reservoir of water with distinct boundaries is clear presented. The output pan-sharpened Landsat images obtained from the four pan-sharpening techniques are assessed both visually and quantitatively.

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3.1. Visual Evaluation

The visual performances of the panshrpening images of the first case study are shown in Figure 2. The merged image's spatial details are pretty well enhanced using Gram, Brovey, and IHS methods. The edges of fields and the course of the river are sharper, but there are some changes in the color tones in the Brovey method while in the PCA method the spatial details are enhanced with color changes, especially in the area surrounding the river.
For the second case study, figure 3 presents the panshapening for the four selected techniques. All techniques lead to sharper details and improved clarity where features such as roads, fields, and water bodies appear sharper and more defined while preserving the original color information in Gram and IHS methods. In the Brovey method, the spectral balance has changed, leading to a more pronounced change in color appearance, as seen in the increased contrast and slightly shifted hues. Also, with the PCA method, although the features such as roads and edges are clear but still be some shifts in hue or contrast.

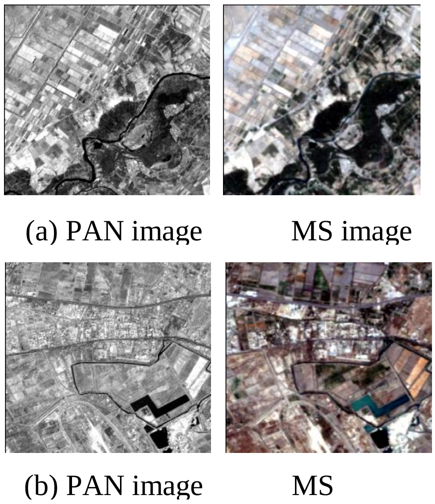

Figure 1. (a) The PAN and MS images from path 168, row 36 (1st case study). (b) the PAN and MS images from path 168, row 37 (2nd case study).

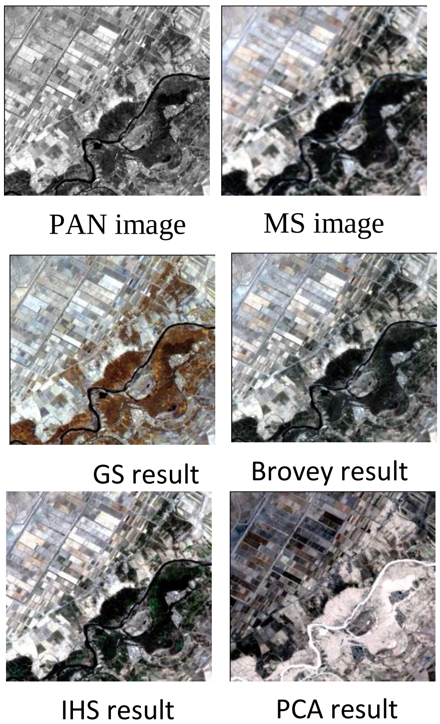

Figure 2. The result of applying the CS methods of first case study (168, 36)

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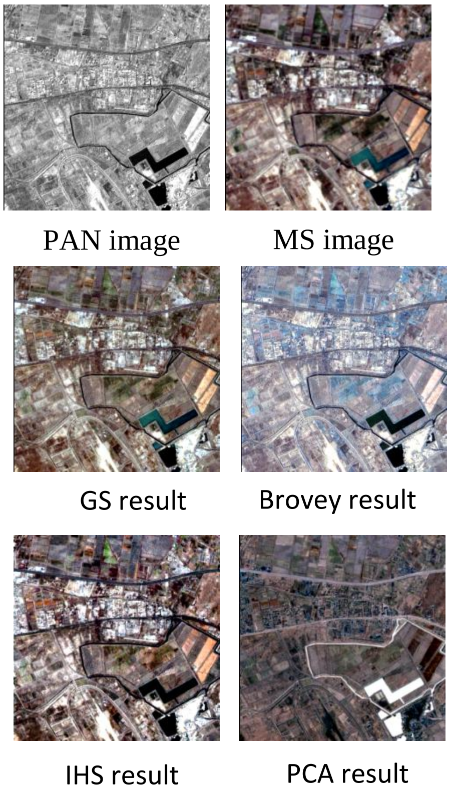

Figure 3. The result of applying the CS methods of second case study (168,37)

3.2. Quantitative Evaluation

In order to achieve further precise evaluation criteria, application results on selected satellite images for the two study areas are quantitatively evaluated from the aspects of Correlation Coefficient (CC), Spectral Correlation Coefficient(sCC), Root Mean Square Error (RMSE), and Relative Average Spectral Error (RASE) Correlation Coefficient (CC). The CC metric quantitatively assesses the direction and magnitude of the linear relationship between the enhanced image and the source or reference image. When using an MS image as a reference image, the CC shows the spectral integrity, while if higher spatial image is used, then the CC will be the spectral correlation coefficient (sCC). The range value of CC is between -1 to +1 and ideal value is +1, which indicates the high similarity between the reference and enhanced images. To calculate CC, the following formula is utilized [18,24,25,26]:

$$CC = \frac{\sum_{i=1}^{N}\sum_{i=j}^{N}(MS_{i,j}-\overline{MS})\,(E_{i,j}-\bar{E})}{\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}(MS_{i,j}-\overline{MS})^{2}\,\sum_{i=1}^{N}\sum_{j=1}^{N}(E_{i,j}-\bar{E})^{2}}} \qquad (3)$$

Where

CC is the correlation Coefficient, MS, E, represent the source image and enhanced image and their means respectively.

The quality of the pansharpening results can be evaluated using Root Mean Square Error (RMSE). The following equation is used to calculate the RMSE [27].

$$RMSE = \sqrt{\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(MS - E)^{2}} \qquad (4)$$

Relative Average Spectral Error (RASE): This metric is obtained from RMSE, and it is applied to assess the average performance of the panshapening method for each spectral band where the success of RASE increases as the numerical value decreases. The formula of RASE is

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$$RASE = \frac{100}{\bar{X}} \sqrt{\frac{1}{L}\sum_{i=1}^{L} RMSE^2(B_i)} \qquad (5)$$

M = Mean radiance of each spectral band, N = total number of spectral bands, Bi = spectral bands of MSI, SD = standard deviation. Where X presents the average radiation value of L band of original multispectral image [3,28,29].

Table 1 presents the performance comparison, in **Correlation Coefficient (CC)**, the Gram method has the highest CC (0.98), followed by HIS (0.97) which indicating that these methods produce results closely aligned with the original data. Also, Brovey and PC methods have significantly lower CC values (0.78 and 0.77, respectively), suggesting poorer performance. For Spectral Correlation Coefficient (sCC) similar trends have been observed, with the Gram method (0.78) performing best and Brovey (0.65) and PC (0.63) showing weaker performance. With **Root Mean Square Error (RMSE)**, the Gram method again has the lowest RMSE (15.34), indicating it has the least deviation from the original data, HIS Shows a RASE of **13.46**, which is lower than that of the Gram method but still acceptable and both Brovey and PC methods exhibit higher RMSE values (25.45 and 25.66, respectively), suggesting more noteworthy errors in spectral representation. Finally, **Relative Average Spectral Error (RASE)** metric, Gram method once more performs best with a RASE of 14.65 followed by HIS with 1346, while Brovey and PC show higher values (24.89 and 24.67). Overall, Brovey method uses a simple ratio approach that may not effectively capture the complex relationships between spectral bands, leading to poorer detail preservation and this method may introduce significant color distortions, especially in areas with high spectral variation, affecting overall image quality. Similarly و PC method data transfer into a new space, which can cause a loss of original spectral information and details that are crucial for accurate representation.

Table 1: The quantitative results using three metrics (CC, sCC, RMSE and RASE)

Pansharpening Method	Metrics			
	CC	sCC	RMSE	RASE
Gram	0.98	0.78	15.34	14.65
HIS	0.97	0.76	15.98	13.46
Brovey	0.78	0.65	25.45	24.89
PC	0.77	0.63	25.66	24.67

4. Conclusion

There are diverse methods that can be implemented as satellite image enhancement techniques. However, choosing a suitable method between many methods can be challenging. The image type, the type of sensor used to capture the satellite images, and the applications for which it is to be used all affect the method used to enhance the captured images. This work implements four CS pansharpening methods on two case studies of Landsat 7 images. The experimental results demonstrate that the Gram method consistently outperforms all other methods across all metrics (CC, sCC, RMSE, RASE), indicating it is the most effective pansharpening technique for preserving details and minimizing errors. HIS method also performs well but does not match the Gram method's effectiveness and the Brovey and PC methods demonstrate significantly poorer performance, with higher RMSE and RASE values, indicating they are less reliable for high-quality pansharpening tasks. For future works a hybrid, pansharpening methods can be developed that combine the strengths of the Gram and HIS techniques. This could lead to improved performance by leveraging the detail preservation of the Gram method while addressing its limitations. Also, investigate the application of deep learning techniques for pansharpening. Convolutional Neural Networks (CNNs) or Generative Adversarial Networks (GANs) could be trained to enhance satellite images, potentially outperforming traditional methods.

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