PRODUCING HIGH RESOLUTION SPECTRAL BANDS FROM LOW RESOLUTION MULTI-BANDS IMAGES, USING PRINCIPAL COMPONENT ANALYSIS "PCA" TECHNIQUE

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Abstract

Image data fusion is the process of setting together information gathered by different heterogeneous sensors, mounted on different platforms. This research presents an effective multi-resolution image data fusion methodology, which is based on utilizing the Principal Component Analysis "PCA". The first principal component "PCA1" involves much of the variability in the spectral data; while the reminder PCAs contain the remaining variability in a descend order. The low resolution multispectral bands are, firstly, resized (i.e. enlarged) into the high resolution "panchromatic" image size, then transformed into several PCAs. As first step the panchromatic image is normalized to have the same number of gray levels as the PCA1, then replacing the PCA1 of the low- resolution-multispectral image in the PCA transformed domain. The high-resolution-multispectral images are produced by inversely transform the modified PCA's file.

إنتاج حزم طيفية عالية التحليل من صور واطئة التحليل متعددة-الحزم بإستخدام تقنية تحليل العناصر الأساسية "PCA"

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الخلاصة

تعتبر دمج بيانات الصور من العمليات الخاصة بتوحيد المعلومات المستحصلة من متحسسات متنوعة منصوبة على منصات مختلفة. في هذا البحث تم تقديم طريقة دمج كفؤة لتوحيد بيانات الصور، تستند على تقنية تحليل العناصر الأساسية. يتضمن العنصر التحليلي الأول على كمية كبيرة من التغيرات في البيانات الطيفية، بينما تتضمن العناصر الأخرى متغيرات طيفية تتناقص بشكل إنحداري منظم. العملية الأولى في هذه التقنية تتضمن أعادة تحجيم الصور الواطئة التحليل (أي تكبيرها) لتتخذ حجم الصور العالية التحليل، بعدها يتم تطبيق تحويلة تحليل العناصر الأساسية. الخطوة التالية تتضمن تطبيع أو تعيير الصور العالية التحليل لتستبدل محل العنصر التحليلي الأول في ميدان التحويل للعناصر الأساسية. يتم بعدها إنتاج الصور المتعددة الحزم ذات القدرات التحليلية العالية بتطبيق التحويل المعاكس على ميدان العناصر المحورة.

Introduction

In recent years, many solutions for multi-resolution image data fusion have been proposed, for instance see [1-6]. In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in remote sensing require high spatial and high spectral resolutions being existed in a single image. Most of the available equipments are not capable to provide such data. Therefore, image fusions may be used to provide the integration of different information sources; i.e. the fused image can have complementary spatial and spectral resolution characteristics. Generally, the standard image fusion techniques distort the spectral information of the multispectral data; mostly they fall into two categories; i.e. ***feature space*** and ***spatial domain*** techniques, [7]. The feature space fusion is performed by transforming the multispectral images into a new space in which one image represents the correlated component; e.g. the PCA1, using the PCA transformation, or adopting the intensity in a space created with Color-Space Transform (CST). In both these methods, the correlated component is replaced by the higher resolution image and transforms the result back to the image space. However, the spatial domain fusion techniques transfer the high-frequency contents of the higher-resolution image to the lower resolution image. In best cases, the mentioned methods have not satisfied enlargement more than 7.5:1 times [7].

Normally, the problem of image data fusion comes when different sensors imaging the same object and we try to obtain a result that integrates the best characteristics of each of those sensors. In this research, to overcome this problem, our fusion technique will concern on improving both the spatial characteristic (utilizing the PCA method), and enhancing the spectral characteristic (using the HM method).

The PCA Transformation:

As mentioned above, the PCA is a feature space transformation method designed to remove the redundancies existed between similar functions or images. It is a linear transform of the type, [7].

$$PCA = W_{PCA} . Y \qquad (1)$$

Where; *PCA* is the output principal component vector, *Y* is the image spectral vector, and W_{PCA} is a weight matrix, referred as the transformation kernel, represented as;

$$W_{PCA} = \begin{bmatrix} e_1^T \\ . \\ . \\ e_K^T \end{bmatrix} = \begin{bmatrix} e_{11} & . & . & e_{1K} \\ . & & & . \\ . & & & . \\ e_{K1} & . & . & e_{KK} \end{bmatrix} \qquad (2)$$

Where: e_{ij} is the j^{th} element of the i^{th} covariance matrix eigenvector.

This transformation kernel alters the covariance matrix *C* as follows;

$$C_{PCA} = W_{PCA} C W_{PCA}^T = \begin{bmatrix} \lambda_1 & . & . & . & 0 \\ . & \lambda_{21} & . & . & . \\ . & . & \lambda_3 & . & . \\ . & . & . & . & . \\ 0 & . & . & . & \lambda_K \end{bmatrix} \qquad (3)$$

The zero values of the off-diagonal elements refer to that; the elements of the *PCA* vectors are uncorrelated. Keep in mind that λ_K are the eigenvalues of *C* can be found as the roots of the following characteristic equation, [7];

$$| C - \lambda I | = 0 \qquad (4)$$

Where: *I* is the diagonal identity matrix.

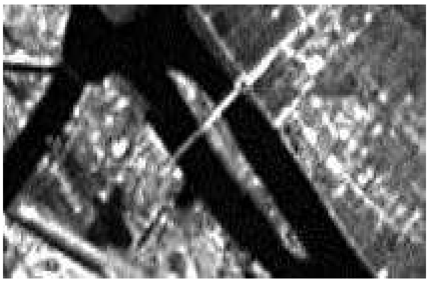
The *PCA* coordinate axes are defined by the *K* eigenvectors e_K, that can be obtained from the following vector-matrix equation, for each eigenvalue $\lambda_{i;}$; i.e.

$$| C - \lambda_i I | e_i = 0; \quad for \ \ i = 1, 2, ..., K \qquad (5)$$

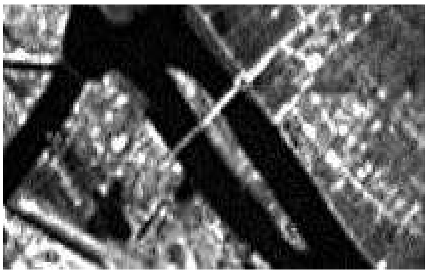
Samples of the used Images:

The samples of images used in this research, as shown in figures below, represent the Sindbad Island at Basra Province, South of Iraq with different spatial resolutions. The study area lies between the latitudes 30.582647°N to 30.568133°N and longitudes 47.761367°E to 47.792122°E, using UTM projection, WGS84 Datum (Zone 38 Northern Hemisphere), and covering an area of 4.72 km^2.

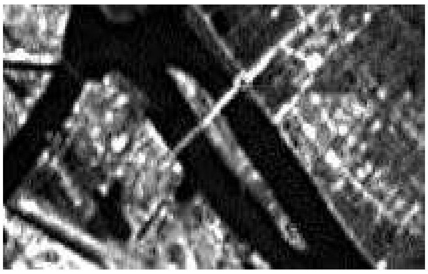
The low-resolution-multispectral bands (Red 0.63-0.69 µm, Green 0.52-0.6 µm, Blue 0.45-0.52 µm), acquired by Landsat-7 satellite imagery with the Enhanced Thematic Mapper "ETM$_+$" sensor, of spatial resolution 14.25m, the combination of their true coloring bands and its histograms are shown in (Figure 1-a), their histograms are illustrated in (Figure1-b). The high-resolution image, representing the same Landsat-7 area, acquired by QuickBird satellite imagery, pan-sharpened with 0.6m resolution is shown in (Figure 2-a), its histogram is illustrated in (Figure 2-b).



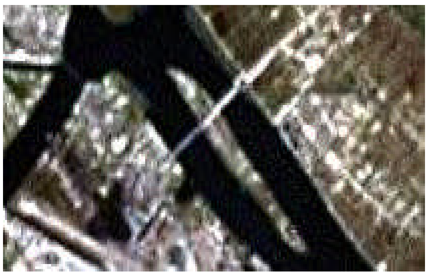
Red band



Green band



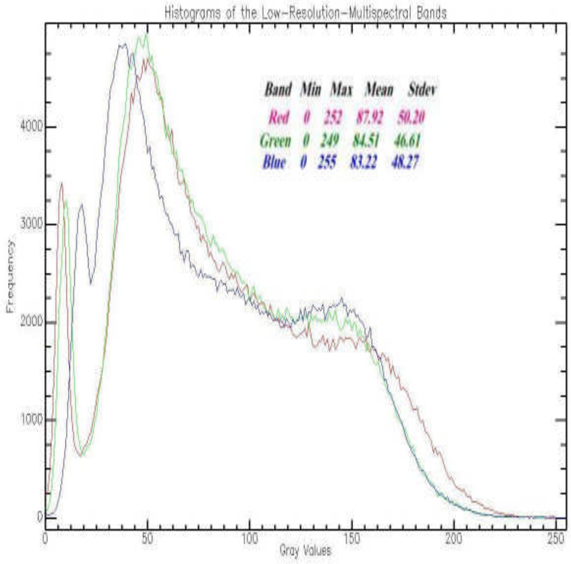
Blue band



RGB colored image

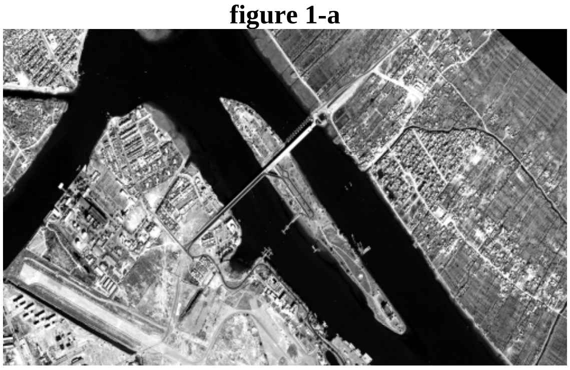
(a)

Figure 1-a: The ETM$_+$ multispectral low-resolution Bands (each of size 211× 109 pixels), and their color combination



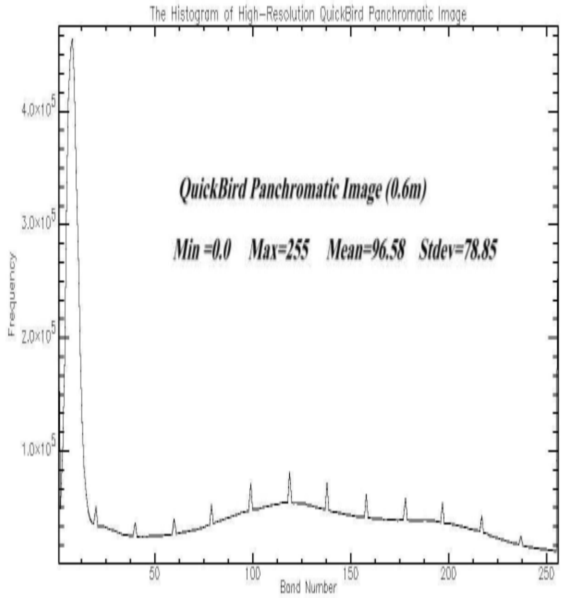
(b)

Figure 1-b: Histograms of RGB bands shown in figure 1-a



(a)

Figure 2-a: The high-resolution QuickBird panchromatic image (size 4985× 2562 pixels).



(b)

Figure 2-b: histogram of the QuickBird image shown in fig.2-a.

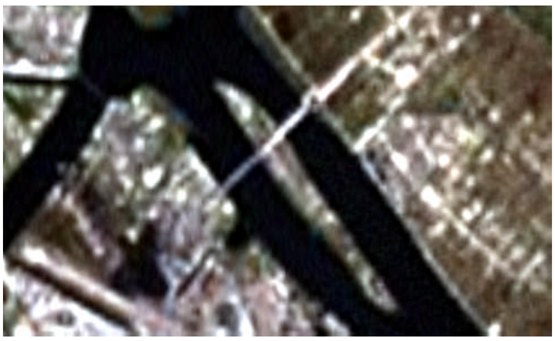
Experimental Results

As it has been mentioned in the abstract, the first step is to resize the low-resolution-multispectral bands to have the same size as the high-resolution panchromatic image. The smaller size (211× 109 pixels), lower resolution multispectral image shown in (Figure 1) has been resized (i.e. enlarged) to the higher resolution panchromatic size (4985 × 2562 pixels), using the ***bilinear methodology***, shown with its histogram in (Figure 3).

The principal components of the resized bands have been computed (their characteristics are listed in Table-1), and illustrated in (Figure 4). To produce the high-resolution-multispectral bands, the first principal components "PCA1" shown in (Figure 4) should be replaced by the renormalized version of the QuickBird image shown in (Figure 2). Let $f_{in}(x, y)$ and $f_{out}(x, y)$ represent, respectively, the original and the normalized QuickBird image gray values, using

$$f_{Out}(x,y) = \frac{f_{in}(x,y) - Min_{QuickBird}}{Max_{QuickBird} - Min_{QuickBird}} \times (Max_{PCA1} - Min_{PCA1}) + Min_{PCA1} \qquad (6)$$

The histograms of the original and the normalized QuickBird images, using equations (6), are shown in (Figure 5). High resolution multispectral QuickBird bands can be produced by replacing the PCA1 image by the normalized QuickBird image, and performing PCA's inverse transformation, as illustrated in (Figure 6), their histograms are shown in (Figure 7).



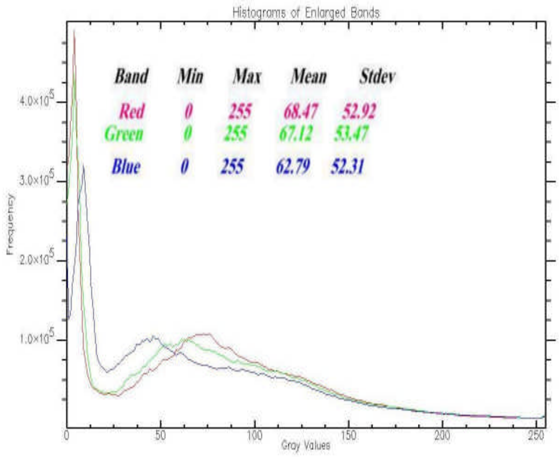
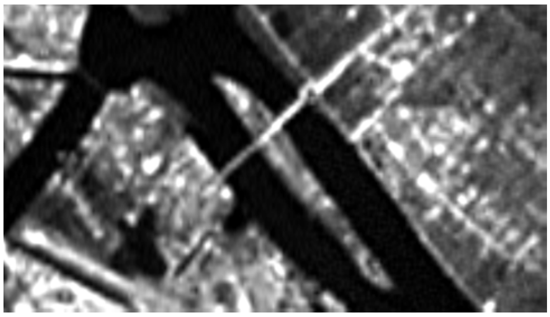
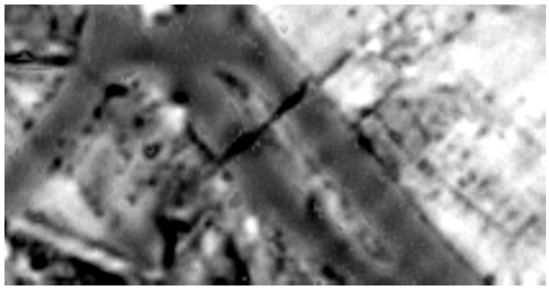


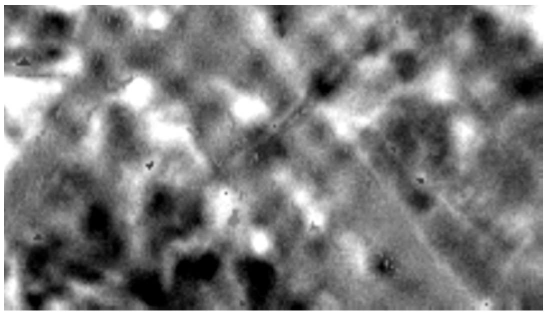
Figure 3: The Enlarged version of the lower-resolution image shown in figure 2.



PCA1



PCA2



PCA3

Figure 4: Three principal Components of the enlarged bands of the low-resolution-multispectral bands.

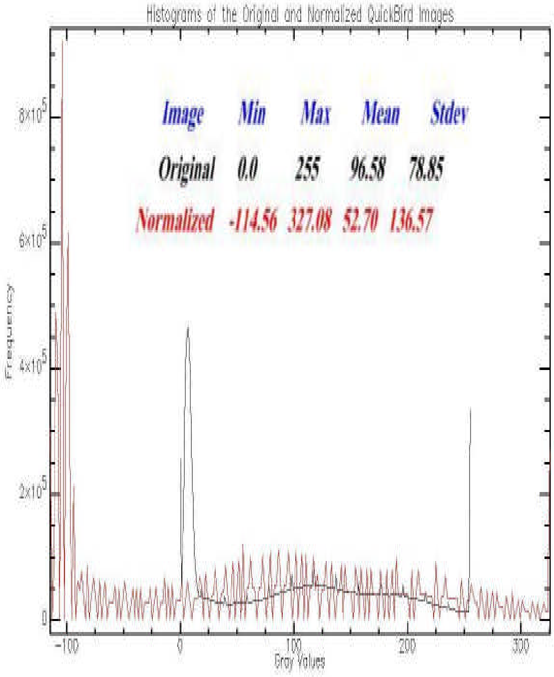


Figure 5: The histograms of the original and normalized QuickBird images.

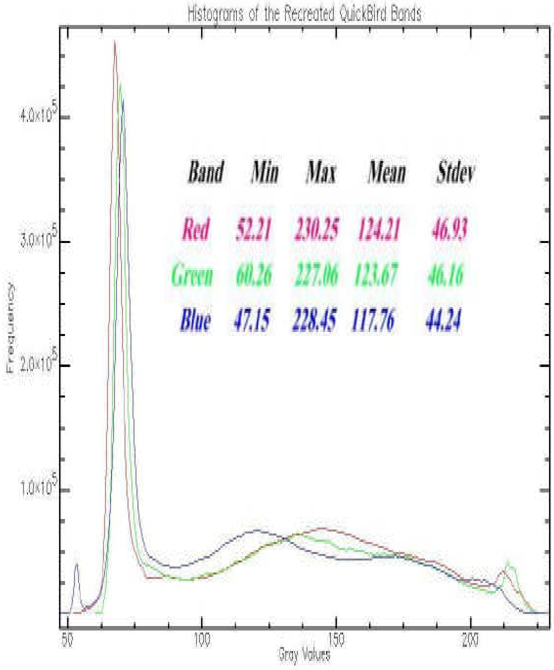


Figure 7: Histograms of the recreated QuickBird Bands.

Figure 6: The recreated QuickBird bands (SR 0.6m) of Sinbad scene.

Table 1: The PCA's characteristics of the enlarged bands.

PCA	Min	Max	Mean	Stdev	Eigenvalue λ_i	Energy $\lambda_i/\lambda_{total}$
1	-114.563957	327.079712	0.0	91.240669	8324.859627	99.14%
2	-27.828854	20.280409	0.0	8.001491	64.023864	0.76%
3	-11.599282	14.752604	0.0	2.901126	8.416529	0.10%
Total					8397.30002	100%
Note: last column represent the amount of image information that can be obtained by adopting each of the PCA in an inverse PCA's transformation process.						

Conclusions:

An efficient method for data fusion is presented. Image histograms showed that the introduced results are much better than those obtained by utilizing the mean-ratio as normalizing criterion, see [4]. However, despite the very encouraging results obtained by this data unification method, it is still more works are required to push the produced high resolution bands as the lower resolution bands. Most of the published papers we have checked have been performed on images of contiguous spatial resolution, while our introduced method dealt with image bands having spatial resolutions differ by 23.75 times.

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