MULTI-SENSOR IMAGE FUSION BY INVERSE SUBBAND CODING

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ABSTRACT

Efficient multi-resolution image fusion aims to take advantage of the high spectral resolution of Landsat TM images and high spatial resolution of SPOT panchromatic images simultaneously. This paper presents a multi-resolution data fusion scheme, based on subband image decomposition. Motivated by analytical results obtained from high-resolution multispectral image data analysis: the energy packing the spectral features are distributed in the lower frequency subbands, and the spatial features, edges, are distributed in the higher frequency subbands. This allows to spatially enhancing the multispectral images, by adding the high-resolution spatial features (extracted from the higher subbands of a panchromatic image) to them, in an inverse subband coding procedure. This technique finds application in multi-spectral image interpretation, as well as medical images of the same part of body obtained by several different imaging modalities. In this paper, the low resolution Landsat Thematic Mapper images (with 30-m and 75-m pixel size) are spatially enhanced to the 10-m resolution by fusing them with the 10-m SPOT panchromatic data. This method is compared with the IHS and PCA and the Brovey transform methods. Results show it preserves more spectral features with less spatial distortion.

1 INTRODUCTION

The aim of remote sensing is acquisition and interpretation of spectral measurements made at a distant location, to obtain information about the Earth's surface. In order to produce a high accuracy map, the classification process assigns each pixel of the image to a particular class of interest. In remote sensing systems pixels are observed in different portions of electromagnetic spectrum, therefore the remotely sensed images are vary in spectral and spatial resolution. To collect more photons and maintain image SNR, the multispectral sensors (with high spectral resolution and narrow spectral bandwidth) have a larger IFOV (i.e. larger pixel size and lower spatial resolution) compared to panchromatic with a wide spectral bandwidth and smaller IFOV (higher spatial resolution) sensors. With appropriate algorithms it is possible to combine these data and produce imagery with the best characteristics of both, namely high spatial and high spectral resolution. This process is known as a kind of multisensor data fusion. The fused images may provide increased interpretation capabilities and more reliable results.

Multisensor image fusion combines two or more geometrically registered images of the same scene into a single image that is more easily interpreted than any of the originals. This technique finds application in remotely sensed multispectral image data interpretation, and they are performed at three different processing levels according to the stage at which the data fusion takes place; are named, pixel level, feature level and decision level (Pohl 1998). At the pixel level, which is the lowest processing level, the measured physical parameters by sensors are merged together (Figure 1). At this level, the higher resolution image is used as the reference to which the lower resolution image is geometrically registered. Therefore, the lower resolution image is up sampled to match the ground sample interval of the higher resolution image. In addition the resampling process, the images must have some reasonable degree of similarity; thus this process requires radiometric correlation between the two images. At the feature level, image fusion requires a robust feature selection scheme for the multisensor images and a sophisticated feature extraction technique (Figure 2). The proposed method in this paper is a feature level image fusion technique. And finally, the decision level image fusion represents a method that uses value-added data where the input images are processed individually for classification (Figure 3).

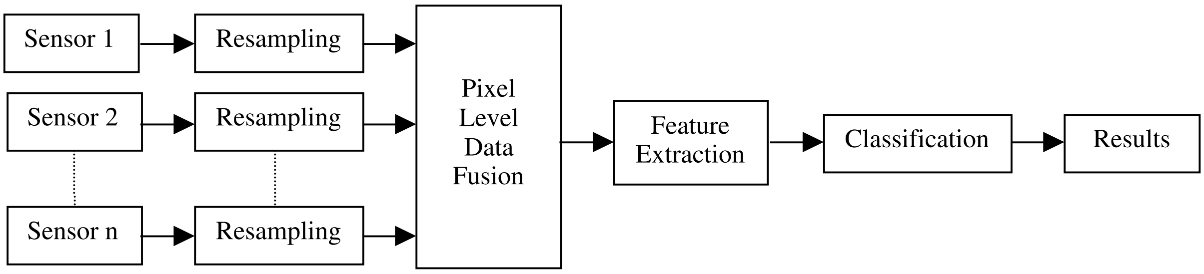

Figure 1. Pixel level multisensor image fusion procedure

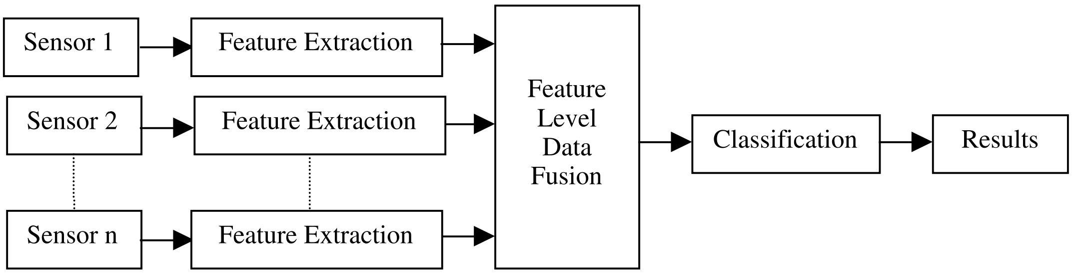

Figure 2. Feature level multisensor image fusion procedure

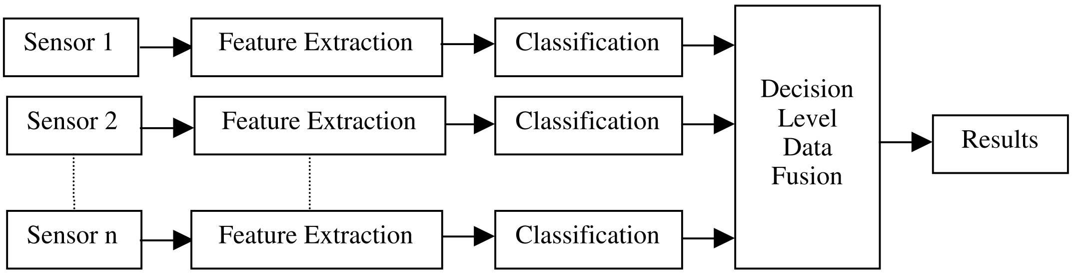

Figure 3. Decision level multisensor image fusion procedure

The objective of the multisensor image fusion is to generate hybrid high spatial resolution multispectral images that attempt to preserve the radiometric characteristics of the original low spatial resolution multispectral data. For example, the combination of SPOT panchromatic image data, having a spatial resolution of 10m, with Landsat Thematic Mapper images, having six spectral bands at 30-m resolution, can provide a hybrid image having a good spatial detail, and useful spectral information for identification of small stands of species, which is not possible from neither the Landsat nor SPOT images.

There are many algorithms for spatially enhancement of low-resolution imagery by combining of high and low resolution data. Some widely performed in the remote sensing community are intensity-hue-saturation, IHS, principal component analysis, PCA, and the Brovey transform (Chaves 1991). Recently, the wavelet transform has been used for merging multiresolution images. A quantitative comparison has been done, in both spectral and spatial features, to evaluate the wavelet transform and other traditional algorithm in (Zhou 1998).

All of the above methods are performed in the pixel level of multisensor image fusion. The objective of this paper is to present a new feature based multisensor image fusion technique, to merge low-resolution multispectral images with high-resolution panchromatic image, and compare the results with those of pixel based methods. This paper is organized as follows. In section 2, three pixel level image fusion methods are reviewed. The proposed feature based multisensor image fusion is introduced in section 3. In section 4, experiments of using the above methods for merging the six TM images of Tehran and the SPOT panchromatic image of the same area are presented. And finally, the spectral and spatial quality of the fused images is compared in section 5.

2 PIXEL LEVEL IMAGE FUSION METHODS

Three famous and commonly used, pixel level, image data fusion methods are based on IHS, PCA and Brovey transforms. Image registration is the first and important preprocessing stage of the multisensor image fusion by the IHS, PCA and Brovey methods. At this stage the images should cover the same geographical area and have 100% of overlap. The higher resolution image, SPOT panchromatic image, is used as the reference to which the lower resolution images, TM images, are geometrically registered. The lower resolution images (six bands of TM with 30m resolution) are up sampled to match the ground sample interval of the higher resolution image (SPOT panchromatic image with 10m spatial resolution).

2.1 Intensity-Hue-Saturation Transform Method

Intensity, Hue and Saturation refer to the parameters of human color perception. Intensity refers to the total brightness of a color. Hue refers to the dominant or average wavelength of light contributing to a color, when applied to data displayed on an RGB monitor, hue can be described on a circular scale progressing from red to green to blue and back to red. Saturation specified the purity of a color relative to gray; vivid colors are highly saturated while pale, pastel colors have low saturation. The IHS model defines colors on the equal intensity planes as coordinates of hue and saturation, with hue being measured as an angle around the plane and saturation as the radial distance from the center of the plane (Pratt 1991). IHS cylindrical coordinates can be computed from RGB Cartesian coordinates:

$$I = \frac{TM_i + TM_j + TM_k}{\sqrt{3}} \tag{1}$$

$$H = \tan^{-1}\left(\frac{v_2}{v_1}\right) \tag{2}$$

$$S = \sqrt{v_1^2 + v_2^2} \tag{3}$$

Where

$$v_1 = \frac{TM_i + TM_j - 2TM_k}{\sqrt{6}} \quad \text{and} \quad v_2 = \frac{TM_i - TM_j}{\sqrt{2}} \tag{4}$$

This transform can fuse any three bands of TM with SPOT PAN at one time. Three TM bands are transformed from RGB coordinates to IHS coordinates, and then the SPOT PAN is stretched linearly so that it has the same mean and variance as the intensity image has. Finally the intensity image is replaced by this stretched image and the new IHS images are transformed back into RGB coordinates. The new spatially enhanced TM images can be computed by the inverse transform given in equation (5).

$$\begin{pmatrix} TM_i^h \\ TM_j^h \\ TM_k^h \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} & \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{-2}{\sqrt{6}} & 0 \end{pmatrix} \begin{pmatrix} I \\ S\cos(H) \\ S\sin(H) \end{pmatrix} \tag{5}$$

2.2 Principal Component Analysis Transform Method

The Principal Component transformation (also referred to as eigen value, Hotelling or discrete Karhunen-Loeve transforms) uses spectral statistics of the image to define a rotation of the original image such that the data are arranged along axes of decreasing variance. The coordinates for new axes are computed by an affine transformation of the original data coordinates. PCA is a very useful tool for multispectral remote sensing data analysis, especially for image data compression. It conducts a linear transformation of the multispectral space (measure space) into the eigen vector space (feature space). Let X be an n-dimensional vector, and represent the multispectral observation of a pixel of the scene. The principal component transform is defined by:

$$Y = A^T X \tag{6}$$

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

$$C_y = E\{(Y - m_y)(Y - m_y)^T\} = AC_x A^T = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} \tag{7}$$

Where $\lambda_1 > \lambda_2 > \ldots > \lambda_n$ are the eigen values of the covariance matrix of X. The result of the principal component transform is a set of uncorrelated images whose variances of the images' energies are ordered in amplitude.

By using PCA the six TM multispectral bands are transformed into the six independent principal component images. The first principal component image PC1, contains the information that is highly correlated to the six bands used as input to PCA, while spectral information unique to any of the bands is mapped into other components. Then the first principal component PC1 is replaced by SPOT PAN image, which is first stretched to have the same mean and variance a PC1. Finally, performing an inverse PCA transform, given by equation (8), derives the merged TM images:

$$X = A^{-1} Y \tag{8}$$

2.3 Brovey Transform Method

The Brovey transform is a simple method to merge data from different sensors. This transform is introduced by Earth Resource Mapping PTY LTD in the ER Mapper 5.0 reference book 1995. It applied to Landsat TM images to merge with SPAT PAN image, the formula used, in this research, are given in the following equations (Zhou 1998):

$$R = \frac{TM_4}{TM_2 + TM_3 + TM_4} \times PAN \tag{9}$$

$$G = \frac{TM_3}{TM_2 + TM_3 + TM_4} \times PAN \tag{10}$$

$$B = \frac{TM_2}{TM_2 + TM_3 + TM_4} \times PAN \tag{11}$$

3 A FEATURE LEVEL MULTISENSOR IMAGE FUSION

The above methods and several other techniques have been developed to merge high-resolution panchromatic data with low-resolution multispectral data. Normally, the objective of these procedures is to create a composite image of enhanced interpretability, but, those methods can distort the spectral characteristics of the multispectral images and the analysis becomes difficult. Artifacts in the merged images arise from poor spectral correlation. As an example, in fusion of near IR TM images with higher resolution panchromatic image of SPOT. Since the panchromatic band's sensory does not extend into the near IR, images with vegetation will show good correlation between the visible bands and panchromatic band, and poor correlation between the near IR and panchromatic band. Thus, false color IR composites of fused imagery will tend to have artifacts, particularly near vegetation-soil boundaries, where the original image contrast reverses between the visible and near IR bands. To overcome the above problems, this section presents a multi-resolution data fusion procedure, allowing the use of high- resolution panchromatic image while conserving the spectral properties of the original low-resolution multispectral images. It is desirable that this procedure for merging high-resolution panchromatic data with low-resolution multispectral data should preserve the original spectral characteristics of the later as much as possible. The procedure should be optimal in the sense that only the additional spatial information available in higher resolution data is imported into the multispectral bands.

Let the observed scene be an L-m by L-m area on the Earth, the low-resolution (Δ_1) sensor produces an N1 by N1 image, called $f_1(x,y)$, and the high-resolution (Δ_2) sensor generates an N2 by N2 image, called $f_2(x,y)$, (Figure 4). The Fourier transform (as a feature extraction process) of the images in the spatial-frequency domain are given by the following equations:

$$F_1(u,v) = \sum_{y=1}^{N_1} \sum_{x=1}^{N_1} f_1(x\,\Delta_1 + y\,\Delta_1)\, e^{-2\pi j(xu+yv)\Delta_1} \tag{12}$$

$$F_2(u,v) = \sum_{y=1}^{N_2} \sum_{x=1}^{N_2} f_1(x\,\Delta_2 + y\,\Delta_2)\, e^{-2\pi j(xu+yv)\Delta_2} \tag{13}$$

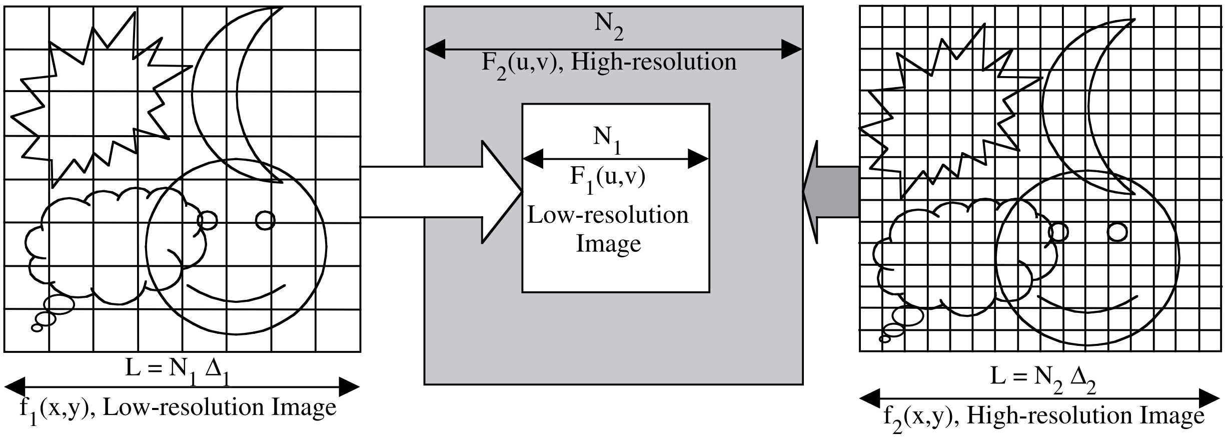

Figure 4. The Fourier transform of multiresolution images

The schematic diagram of the above transform is depicted by Figure 4. It is clear that, the low-resolution image is located in the low-frequency region (up to $N_1\delta$), and the high-resolution image occupies also the higher frequency up to $N_2\delta$, this suggests a multiscale image coding scheme, or multiresolution scene representation (Ghassemian and Landgrebe 1988). This scheme is based on subband image decomposition, motivated by analytical results obtained from high-resolution multispectral image data analysis: the energy packing the spectral features are distributed in the lower frequency subbands, and the spatial features, edges, are distributed in the higher frequency subbands (Ghassemian and Venetsanopoulos1998). This allows to spatially enhancing the multispectral images, by adding the high-resolution spatial features (extracted from the higher subbands of a panchromatic image) to them, in an inverse subband coding procedure.

$$F(u,v) = \sum_{i=1}^{n} H_i(u,v) F_i(u,v) \tag{14}$$

$$f(x\Delta_n, y\Delta_n) = \frac{1}{N_n^2} \sum_{v=1}^{N_n} \sum_{u=1}^{N_n} F(u,v)\, e^{2\pi j(xu+yv)\Delta_n} \tag{15}$$

Figure 5 shows how a multiscale scene can be decomposed into subbands in the spatial-frequency domain, and, a feature level data fusion can then synthesis a multispectral high resolution image of the scene with the spatial resolution of $\Delta_n = L / N_n$.

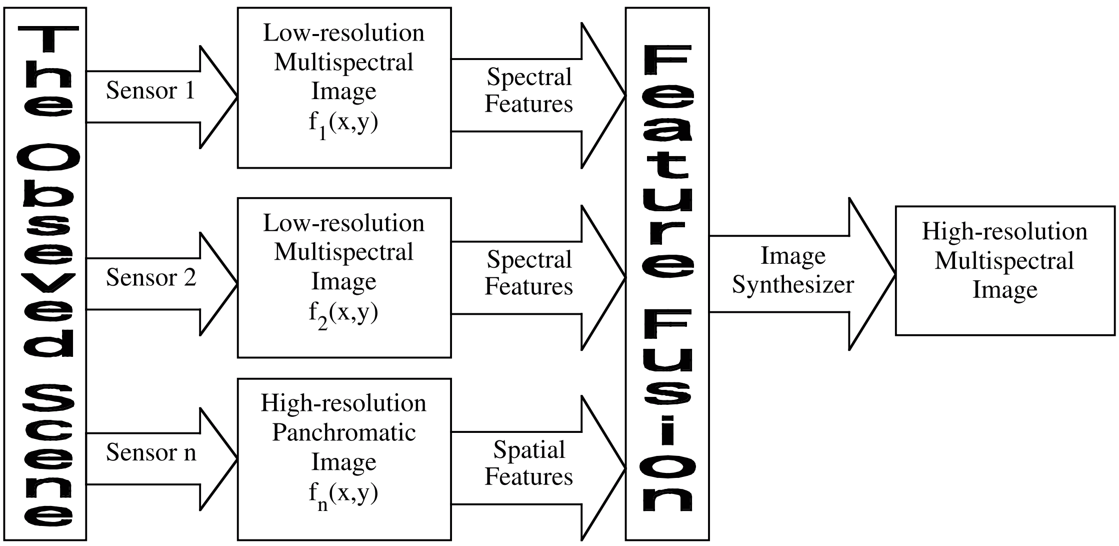

Figure 5. Multisensor image data fusion by the spatial-spectral feature synthesizer

4 EXPERIMENTS

The test area is 10-Km by 10-Km, located in the North-West of Tehran, Iran, which included various land cover types such as: differed urban usage, international airport, natural Park, small lake, agricultural, mountains, bare soil, highways, etc. The images were taken by Landsat satellite on May 1998 and by SPOT satellite on July 1998, provided by Iranian Remote Sensing Center. Figure 6 shows part of the original images of TM bands in RGB color composite (bands 4,3,2).

The TM images were registered geometrically onto SPOT panchromatic as a reference image, by selecting 20 control points. The registration accuracy was lese than 0.75 pixel size. For all merging methods, except our proposed method, the TM images resample to 10-m resolution, by using first order polynomial, and nearest neighbor interpolation algorithm. The IHS and Brovey methods can merge only three multispectral bands with the PAN image; thus the six multispectral bands were divided into two groups and merged separately with the PAN. The combination of TM bands 2,3,4 was selected because these bands most closely covered the same portion of the electromagnetic spectrum as the PAN image has. The other group consisted of TM bands 1,5,7 image (Zhou 1998). The PCA and the proposed methods can merge all multispectral bands with the PAN image at once.

Visual evaluation of the 432-bands and 157-bands color composite images, indicates that the IHS, PCA and Brovey methods change color of the composite images, which means the spectral features are distorted by these methods. Due to limitation of space, only two color composite images are printed in this paper; there are 10 full size images, which will be presented in the Congress. Figure 7 shows a 432-bands color composite image of the enhanced TM data by the proposed method. Color appearance of the natural Park, small lake, agricultural, mountains, bare soil and highways indicating that the spectral features have been preserved by this method. The clearly identify street blocks, the highway and the airplanes in the international airport are indicating additive spatial resolution which is not clear in Figure 6.

The quantitative evaluation of methods can be calculated based on the spectral features performance in the classification results. The data fusion should not distort the spectral characteristics of the original multispectral data. The spectral quality of the spatially enhanced images is measured band by band by the correlation between the pixel value of the original images and the spatially enhanced images, presented in the Table 1.

The spectral performance is calculated by the classification correlation between the original images and the spatially enhanced ones. Classification performance evaluated by using two independent supervised classifies, Maximum Likelihood, Minimum Distance, and by an unsupervised classifier ISOCLASS. The comparison is done with seven land cover classes, bare soil, water, two vegetation covers, two urban structures, and highways were selected. The classification correlation as a quantitative parameter is presented in Table 2.

	TM1	TM2	TM3	TM4	TM5	TM7
IHS	0.634	0.702	0.725	0.541	0.765	0.703
Brovey	0.554	0.632	0.711	0.483	0.730	0.807
PCA	0.897	0.796	0.857	0.653	0.940	0.928
Featurefusion	0.909	0.842	0.913	0.865	0.944	0.927

Table 1. Correlation between the original TM bands and the spatial enhanced TM bands

	MLC	MDC	ISOCLASS
TM432/IHS432	0.519	0.331	0.464
TM432/Brovey432	0.501	0.300	0.407
TM432/ PCA432	0.552	0.387	0.619
TM432/ Featurefusion432	0.639	0.487	0.650
TM751/IHS751	0.585	0.366	0.666
TM751/Brovey751	0.523	0.458	0.650
TM751/ PCA751	0.705	0.560	0.889
TM751/ Featurefusion751	0.733	0.688	0.888

Table 2. Classification correlation between original TM composite and the enhanced TM composite

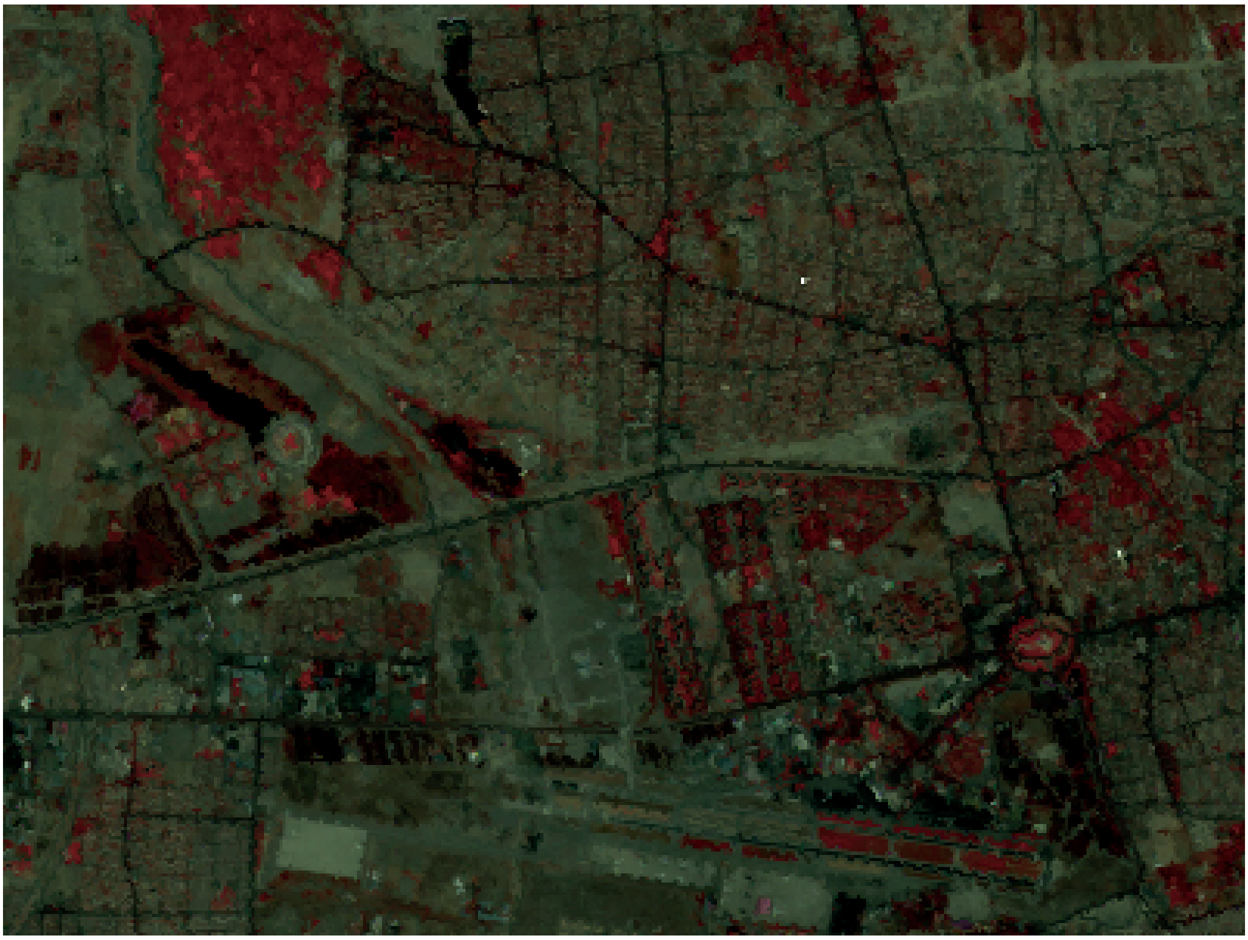

Figure 6. RGB color composite image of the original 4,3,2 TM bands, with 30-m spatial resolution

Figure 7. RGB color composite image of the fused 4,3,2 TM bands, with 10-m spatial resolution

	TM1	TM2	TM3	TM4	TM5	TM7
IHS	0.952	0.921	0.921	0.922	0.934	0.912
Brovey	0.826	0.930	0.938	0.850	0.897	0.909
PCA	0.696	0.863	0.908	0.702	0.585	0.879
Featurefusion	0.976	0.978	0.979	0.977	0.963	0.974

Table 3. Spatial correlation between the original SPOT PAN and the spatial enhanced TM bands

Also the quantitative evaluation of methods can be calculated based on the spatial qualities. The data fusion should not distort the spatial characteristics of the original high-resolution panchromatic data. Spatial quality of the enhanced multispectral images is measured band by band by the correlation between the pixel value of the panchromatic image and multispectral images, presented in the Table 3.

5 CONCLUSIONS

In this paper, a spectral-spatial feature data fusion method has been introduce to spatially enhance the multispectral images. The spatial features were extracted from high-resolution panchromatic image, added to the spectral features of multispectral images by a subband synthesizer. A qualitative and quantitative comparison used to evaluate the spectral and spatial features performance of the proposed method and HIS, PCA, Brovey methods. The following conclusion may be drawn from this research.

Multiscale image fusion is usually a trade-off between the spectral information extracted from multispectral images and the spatial information extracted from high spatial resolution images. The proposed method can control this trade-off. The proposed method achieves the best spectral quality in all bands. Comparing with HIS, PCA and Brovey methods. The best spectral and spatial quality is only achieved simultaneously with the proposed feature based data fusion. In this method, there is no need to resample images, which is an advantage over HIS, PCA and Brovey method, it can performed in any aspect ratio between the panchromatic image and multispectral images' pixels. The resampling procedure degrade the spectral features of the multispectral images in any image merging method, so, it is important to avoid the resampling process as much as possible.

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