OBJECT-BASED IMAGE FUSION METHOD BASED ON WAVELET AND PCA FOR REMOTE SENSING IMAGERY

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KEY WORDS: Object-based image fusion (OBIF), statistical region merging and minimum heterogeneity rule (SRMMHR), Mallat’s, à trous.

ABSTRACT:

In this paper, a new object-based wavelet fusion technique is presented for the fusion of multispectral (MS) and panchromatic (PAN) images to improve spatial information and preserve spectral information. The basic idea is to build a segmented label image by statistical region merging and minimum heterogeneity rule (SRMMHR) segmentation method to guide the object-based image fusion (OBIF). There are three key techniques of the OBIF method including SRMMHR segmentation, Mallat’s and à trous wavelet transformation, and fusion rule based on object energy. The results demonstrate that the new OBIF methods based on wavelet and PCA are better comparing with pixel-based image fusion methods such as Mallat’s, à trous, Mallat’s PCA, à trous PCA.

1. INTRODUCTION

Image fusion is an important tool in remote sensing. As many earth observation satellites provide both high-resolution (HR) panchromatic (PAN) and low-resolution multispectral (MS) images, many fusion methods have been proposed to fuse panchromatic and multi-spectral images to obtain images with high spatial and spectral resolution simultaneously. These methods are divided into three levels including pixel-level, feature-level, and decision-level. Nowadays, most image fusion studies are focus on pixel-level methods. Nevertheless, they have some disadvantages:

(1) They do not consider the spectral, spatial, and radiometric characteristic of various objects of remote sensing imagery synthetically, so the pixel-level fusion methods have no relativity.

(2) They usually fused all the pixels with the same criterion, and only fused between pixel and pixel.

(3) They need higher matching accuracy, when matching accuracy is lower, it is easy to appear skewbald in object boundary and shade region.

(4) It is hard to add “object” concept and find hidden meanings of remote sensing imagery.

There is a great semantic gulf among pixel-level, feature-level, and decision-level. With the development of geographic object-based image analysis (GEOBIA), the technique is applied to image fusion of remote sensing imagery, which is object-based image fusion (OBIF) technique [1]-[7]. It adopts image segmentation technique to segment original imagery into feature objects with different size. Then the feature objects are fused with fusion method and self-adjustable fusion rule. There are three key techniques of the object-based image fusion including image segmentation, fusion method, and fusion rule.

According to the above analysis, the object-based image fusion methods have some advantages as follows:

(1) The process unit is “object” other than “pixel”, which is accord with human’s logical thinking, and is easy to fuse geo-information.

(2) It could control the contribution of different components in the fused product and choose the appropriate fusion rule.

(3) It could eliminate the skewbald which appears in pixel-level fusion, and it is less affected by image matching.

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(4) The self-adjustable fusion rule ensures higher fusion accuracy.

This paper presents a new object-based image fusion method based on Mallat's and à trous wavelet transform. The basic idea is to build a segmented label image based on the synthetical image and use this label image to guide the fusion process.

2. OBJECT-BASED IMAGE FUSION THEORY

2.1 Object-based Wavelet Fusion Frame

Figure 1 shows the frame of object-based wavelet fusion, the key steps are as follows:

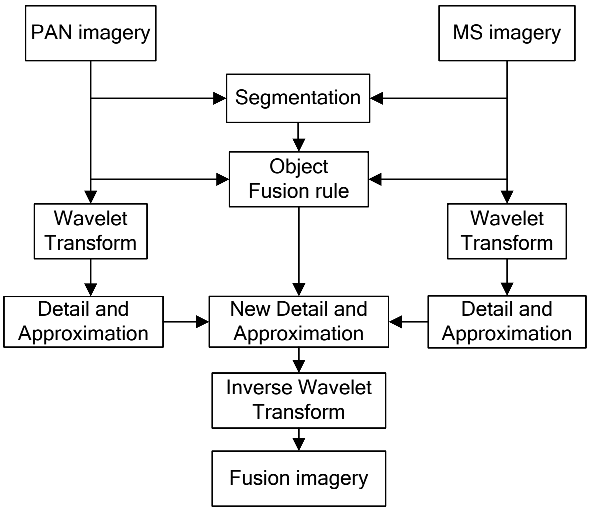

Figure 1. The frame of object-based wavelet fusion.

(1) Image segmentation

The PAN and MS images are split into different regions with various spatial characteristics based on segmentation method. The segmented label image is used as a mapping image of fusion.

(2) Wavelet transform

The PAN and MS images are transformed by Mallat's and à trous wavelet transformation to get detail and approximate images.

(3) Fusion rule

Each particular region of detail and approximate image are fused to get new detail and approximate images by fusion rules such as object energy and object variances.

(4) Inverse wavelet transform

The new detail and approximate images are transformed to get fusion image by inverse wavelet transform.

It is obvious that, image segmentation, wavelet transform, fusion rule are the key steps of object-based image fusion.

2.2 Image Segmentation

Image segmentation is the key step of object-based image fusion for HR imagery. At present, there are thousands of segmentation methods, including edge detection, region-based, pattern recognization, wavelet method and so on. However, not all of the segmentation techniques are feasible for HR imagery.

Considering the characteristics of HR imagery, the commercial software, eCognition, adopts fractal net evolution approach (FNEA) segmentation method which is the best method comparing with other methods in CAESAR3.1, InfoPACK, Erdas Imagine software [9]. Nock and Nielsen [10] presented a statistical region merging (SRM) which not only considers spectral, shape, and scale information, but also has the ability to cope with significant noise corruption and handle occlusions. Based on the SRM and FNEA, the new multi-scale statistical region merging and minimum heterogeneity rule (SRMMHR) segmentation method utilizes the advantages of SRM and FNEA methods [8].

The paper adopted SRMMHR segmentation method, which is composed of two main procedures: the initial segmentation by the improved SRM algorithm and the merging process by the minimum heterogeneity rule (MHR) algorithm. Figure 2 shows the flowchart of the multi-scale SRMMHR segmentation method.

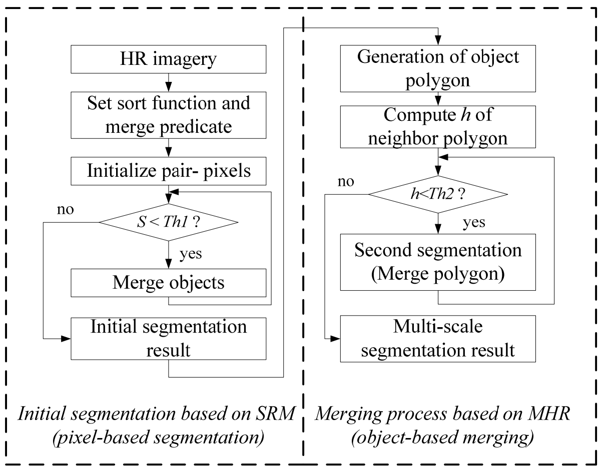

Figure 2. The flowchart of Multi-scale SRMMHR segmentation method.

There are four steps in the initial segmentation progress:

(1) Suppose that the image I contains r rows and c columns. This represents $N=2*r*c-r-c$ couples of adjacent pixels (in 4-connexity). Set the sort function and then sort the N couples of adjacent pixels (pair-pixels) according to the size of

the sort function. Ordering the pair-pixels is a way to eliminate over-segmentation and the hybrid error.

(2) Ascertain the merge predicate which is relative with pair-pixels, and make sure the position of up level nodes the pairs belong to.

(3) Judge whether the seeds of pair-pixels are at the same position, and whether they satisfy the merge predicate. If their positions are not identical and they satisfy the merge predicate($S<Th1$), then the pair-pixels are merged, meanwhile, the area is updated with the sum of the pair-pixels.

(4) Repeat step 2-3 until all the pair-pixels are segmented by the approach. Then an initial segmentation result which is based on pixel-based segmentation is realized.

As to the multi-scale segmentation, there are four steps in the merging progress:

(1) Convert the initial segmentation result into a polygon vector. These results are then saved as a shapefile(.shp) and the associate database file(.dbf) which filled with statistics information about each polygon object (i.e., mean, standard deviation and boundary length).

(2) Set the parameters of Minimum Heterogeneity Rule (MHR), such as weights of colour, shape, compact, smooth, *Th2*. And then compute heterogeneity value h of neighbouring polygon.

(3) Judge whether h satisfy MHR, if $h<Th2$, the adjacent smaller objects are merged into other bigger ones, meanwhile, the average size, standard deviation and mean of all the object regions will be calculated.

(4) Repeat step 2-3 to accomplish multi-scale segmentation.

2.3 Wavelet Transform

Wavelet transformation method is the popular fusion method for fusing HR and MS imagery [11]. The Mallat's and à trous algorithms have been used in remote sensing imagery fusion for several years [12]-[15]. Each one has its particular mathematical properties and leads to different image decompositions. The Mallat's is an orthogonal, dyadic, non-symmetric, decimated, non-redundant discrete wavelet transform (DWT) algorithm. The à trous is a non-orthogonal, shift-invariant, dyadic, symmetric, undecimated, redundant DWT algorithm. In the paper, we used them in the object-based image fusion method.

2.3.1 Mallat's Wavelet

Mallat's wavelet is an important wavelet transform algorithm. Figure 3 describes the stage of 2-D WT with multi-resolution image decomposition (forward wavelet analysis). Figure 4 shows the stage of 2-D DWT with multi-resolution image reconstruction (backward wavelet synthesis).

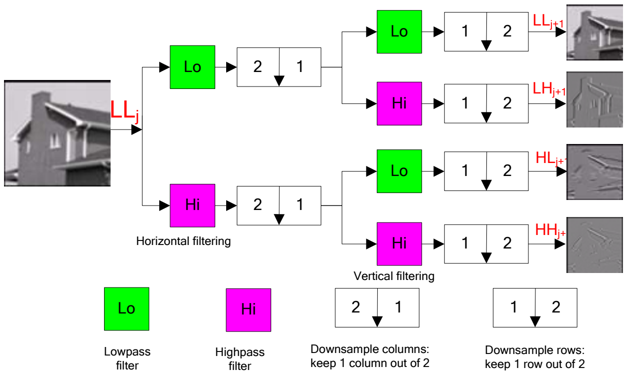

Figure 3. The stage of 2-D DWT by multi-resolution image decomposition (forward wavelet analysis).

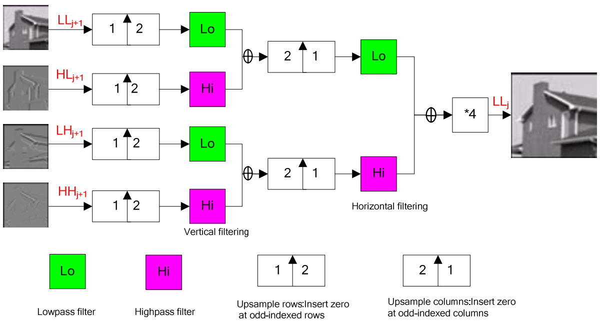

Figure 4. The stage of 2-D DWT by multi-resolution image reconstruction (backward wavelet synthesis).

In the forward wavelet analysis, the original image $A_j f$ is filtered and down-sampled horizontally to each row, and then filtered and down-sampled vertically to each column using low-pass filter *Lo* and high-pass filter *Hi*. The decomposition processing produces four sub-images $A_{j+1} f$, $D^v_{j+1} f$, $D^h_{j+1} f$,and $D^d_{j+1} f$. $A_{j+1} f$ is the coarse approximation. $D^v_{j+1} f$, $D^h_{j+1} f$, and $D^d_{j+1} f$ are the detailed sub-images which represent the vertical, horizontal, and diagonal directions of the original image, respectively.

The backward wavelet synthesis processing is the inverse processing of wavelet analysis. Likewise, the four decomposed sub-images $A_{j+1} f$, $D^v_{j+1} f$, $D^h_{j+1} f$, and $D^d_{j+1} f$ are synthesized to $A_j f$ in the backward wavelet synthesis processing.

2.3.2 à trous Wavelet

In contrast to Mallat's algorithm, the à trous algorithm allows a shift-invariant discrete wavelet decomposition. All the approximation images obtained by applying the decomposition have the same size as the original image. Comparing with other wavelet algorithms, the characters of the à trous wavelet are as follows: (1) It has the characteristic of two-dimensional direction, and is easy to realize by filter. (2) There is no need to down-sampling and up-sampling, and it is easy to get detail information.

Figure 5 shows the à trous decomposition processing. $\{C_0(k)\}$ is the original image, $\{C_1(k)\}$ is the approximation image by scaling function, $\{C_0(k)-C_1(k)\}$ is the detail image (wavelet plane).

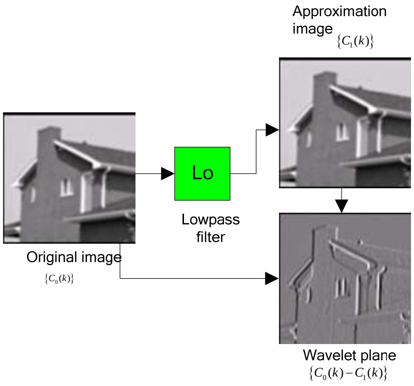

Figure 5. The à trous decomposition processing.

2.4 Fusion Rule

Zeeuw [16] introduced pixel-based fusion rules such as mean, maximum which did not consider the effect of neighboring pixel. Wang, Tang, et.al.[17] presented a region-based fusion method based on wavelet and HIS. But the size of region is fixed with square window size, which did not consider the global character of object, and the same object has different coefficients. In the last years, object energy and match degree have been used in the wavelet fusion [18]. In this work, we use object energy and object match degree to determine fusion rule. In general, the object with larger energy is selected.

(1)Object Energy

The formula of object energy is:

$$E_I(R)=\frac{1}{|R|}\sum_{\vec{N}\in R}E_I(\vec{N}) \tag{1}$$

where, I stands for image X or Y, $\vec{N}=(m,n)\in R$, $|R|$ is the area of region R, $E_I(\vec{N})$ is each pixel energy in region R of image X or Y.

The formula of image energy is:

$$E_I=\sum_{s\in S,t\in T}w(s,t)I(m+s,n+t) \tag{2}$$

where, E_I is the energy of image X or Y, S and T are sets of horizontal and vertical indexes that describe the current window (typically 3 ×3 or 5 ×5), (m,n) stand for the position of pixel, (s,t) stand for moving position, $w(s,t)$ is energy feature operators, $I(m+s,n+t)$ is the pixel value in a small window. In this work, we used $w(3,3)=\{\{0,1,0\},\{1,2,1\},\{0,1,0\}\}$ to compute object energy.

(2) Object Match Degree

The formula of object match degree is:

$$M_{XY}(R)=\frac{1}{|R|}\sum_{\vec{N}\in R}M_{XY}(\vec{N}) \tag{3}$$

where, $\vec{N}=(m,n)\in R$, $|R|$ is the area of region R, $M_{XY}(\vec{N})$ is the match degree between the corresponding pixels in region R in source images X and Y.

The formula of image match degree is:

$$M_{XY}=\frac{2E_XE_Y}{E_X^2+E_Y^2} \tag{4}$$

where, M_{XY} is image match degree between image X and Y, E_X and E_Y are image energy of X and Y.

(3) Fusion rule

The formula of object fusion rule is:

$$D_F(R)=w_XD_X(R)+w_YD_Y(R) \tag{5}$$

where, $D_X(R)$ and $D_Y(R)$ are the wavelet decomposition coefficients of source images X and Y corresponding to R respectively, w_X and w_Y are weights, and $w_X+w_Y=1$.

When object match degree $M_{XY}(R)<\alpha$, the calculation of weights are as equation (6),

$$\begin{cases} w_X=1, w_Y=0, E_X(R)>E_Y(R) \\ w_X=0, w_Y=1, E_X(R)<E_Y(R) \end{cases} \tag{6}$$

when $M_{XY}(R)>\alpha$, the weights are as equation (7),

$$\begin{cases} w_X=\frac{1}{2}-\frac{1}{2}\left(\frac{1-M_{XY}(R)}{1-\alpha}\right), w_Y=1-w_X, E_X(R)<E_Y(R) \\ w_X=\frac{1}{2}+\frac{1}{2}\left(\frac{1-M_{XY}(R)}{1-\alpha}\right), w_Y=1-w_X, E_X(R)>E_Y(R) \end{cases} \tag{7}$$

3 OBJECT-BASED IMAGE FUSION BASED ON WAVELET AND PCA

On the basis of analyzing image segmentation, wavelet transformation, and fusion rule, a new procedure of object-based image fusion method based on wavelet and PCA

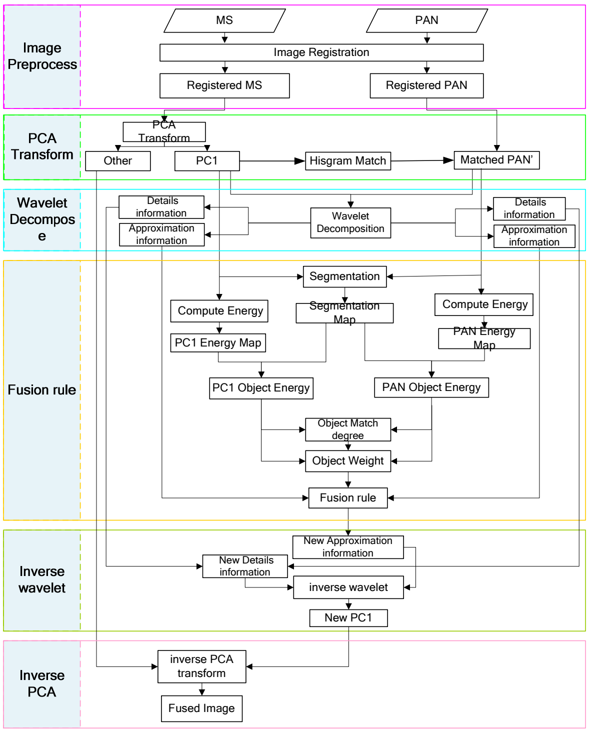

Figure 6. The workflow of object-based image fusion based on wavelet and PCA.

is presented. It applies image segmentation to get objects for fusion rule. The flowchart of the object-based image fusion algorithm is shown in figure 6 which comprises six main components: (1) image preprocessing, (2) PCA transformation, (3) wavelet decomposition, (4) fusion rule computing, (5) inverse wavelet transformation, (6) inverse PCA transformation.

(1) Image preprocessing

The MS image is co-registered to the high-spatial resolution PAN image to get the co-registered images.

(2) PCA transformation

The MS image is transformed by the forward PCA and produces various components such as PC1, PC2, et.al. The first component (PC1) of PCA has the similar gray scale to the PAN image and preserves the detailed space information. Then the PAN image is matched with the PC1 to produce a new PAN image (PAN') which has the similar mean and variance with PC1.

(3) Wavelet decomposition

The new PAN image and PC1 are decomposed to get detail and approximation image by Mallat's or à trous wavelet. As for Mallat's wavelet, we use Daubechies5 to decompose image by first level, the three detail images and one approximation image are half size of the original image. Whereas, by à trous decomposition, the detail and approximation images are the same size as the original image. The key is to choose decomposition level and the wavelet style which affect the fusion results.

(4) Computing fusion rule

As for Mallat's wavelet, the PC1 and PAN' are sampled to half of the original size, and then filtered by $w(3,3)=\{\{0,1,0\},\{1,2,1\},\{0,1,0\}\}$ energy feature operators to get PC1 and PAN' energy maps. Meanwhile, the PC1 and PAN' synthetical image is segmented by SRMMHR method to get segmented label image to guide the fusion process. With these images, object energy is obtained with formula (1), object match degree is obtained with formula (3). Then the object fusion rule is determined by formula (5).

(5) Inverse wavelet transformation

The new detail information is replaced with PAN detail information, the new approximation information is determined by the fusion rule. Then the new detail and approximation information is transformed by inverse wavelet transformation to get the new PC1, which has similar grey value distribution to that of New Pan and contains the same spatial detail of the original PAN image.

(6) Inverse PCA transformation

The new PC1 and other PCA principle components are transformed with inverse PCA transformation to produce the fusion image.

4 EXPERIMENTS

4.1 Experiment Data

To evaluate the performance of the proposed object-based image fusion approach, a MS IKONOS imagery at 4-m resolution and a PAN IKONOS imagery at 1-m resolution, which were acquired in June 2005 in Hebei Province of China. The area is about 890×1514 pixels, the MS imagery was resampled to the same resolution as the PAN imagery. Figure 7(a) shows the high-resolution panchromatic IKONOS image, and Figure 7(b) shows the low-resolution multi-spectral IKONOS image composite of band 3 (red), band 2 (green), and band 1 (blue). Figure 7(c) shows the MS image whose size is the same as the PAN image. Figure 7(d) shows the object-based image fusion based on Mallat's wavelet and PCA. Figure 7(e) shows the object-based image fusion based on à trous wavelet and PCA.

In order to evaluate the performance of the proposed method, we also fused the PAN and MS IKONOS imagery with Mallat's, à trous, "à trous PCA", "Mallat's PCA" pixel-based fusion method. The fusion results are shown in Figure 7(f), Figure 7(g), Figure 7(h), Figure 7(i).

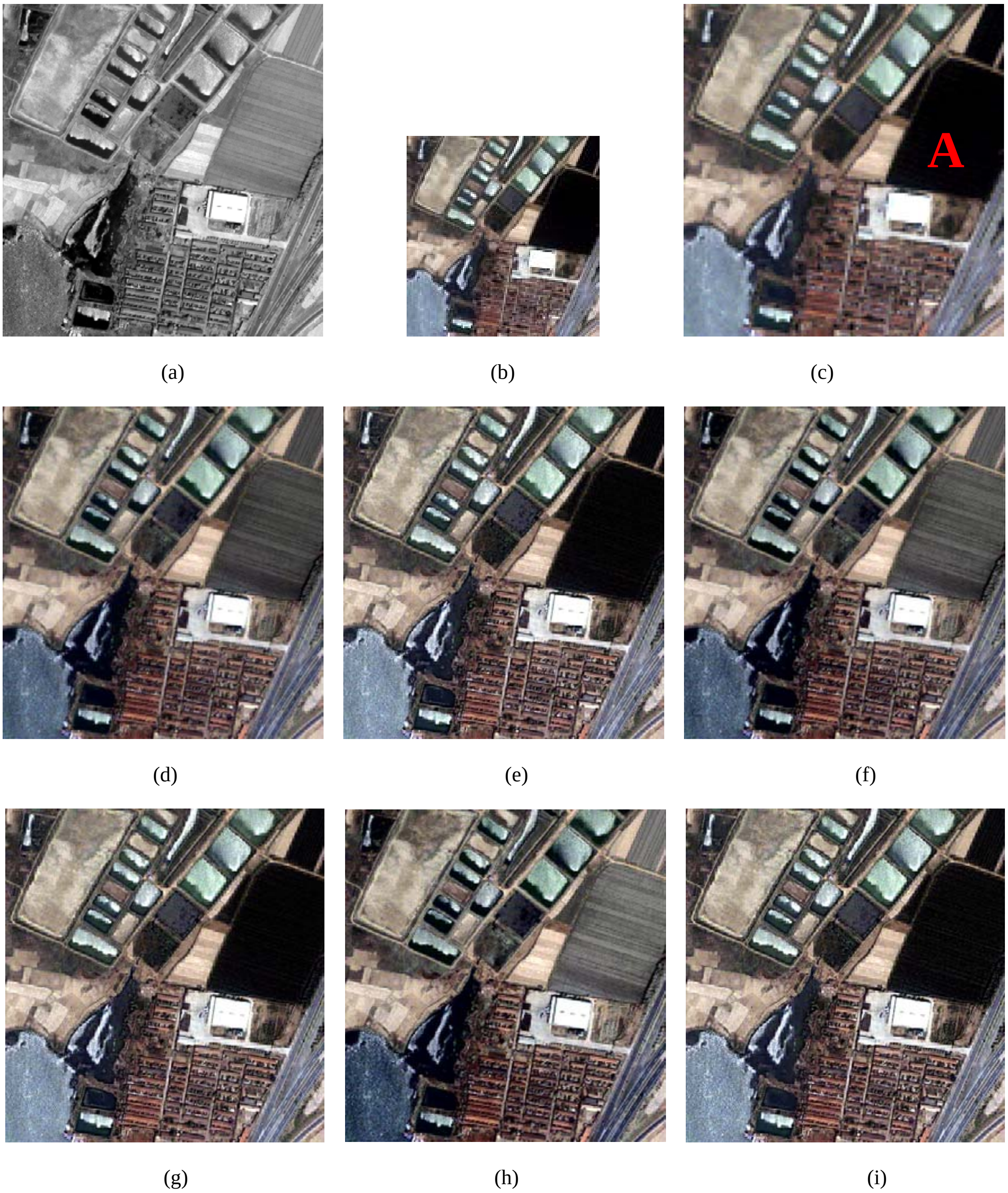

Figure 7. Fused MS images using six fusion methods. (a) High-resolution PAN image. (b) Low-resolution MS images. (c) MS image of the same size as PAN . (d)Object-based image fusion based on Mallat's and PCA. (e) Object-based image fusion based on à trous and PCA . (f) Mallat's. (g) à trous. (h) Pixel -based image fusion based on Mallat's and PCA. (i) Pixel-based image fusion based on à trous and PCA.

4.5 Accuracy Assessment

There are many different performance evaluation indexes to analyze the fusion results [19]-[23].These indexes are mainly divided into three categories which include spatial quality, spectral quality and average indexes to analyze the effect of both simultaneously. In this work, we used the universal image quality index (UIQI), signal noise rate-root mean square (SNR), erreur relative globale adimensionnelle de synthèse(ERGAS), Entropy, to evaluate the fusion results.

The values of evaluation index for various fusion methods were listed in Table 1. From Table 1, we observed that the value of UIQI obtained by object-based image fusion method based on Mallat's and PCA is the highest, the value of SNR obtained by object-based image fusion method based on à trous and PCA is the highest, and the ERGAS value is the lowest. Obviously, the object-based image fusion methods based on wavelet and PCA are better than the pixel-based image fusion methods in a certain degree. The object-based image fusion method based on à trous and PCA is better than that of Mallat's.

Table 1. The values of evaluation index for various fusion methods.

	UIQI	Entropy	SNR	ERGAS
Mallat's	0.818	7.584	6.215	15.452
à trous	0.778	7.223	6.703	14.088
Mallat's PCA (pixel-based)	0.874	**7.621**	6.357	17.890
à trous PCA (pixel-based)	0.769	7.347	6.796	16.778
Mallat's PCA (Object-based)	**0.916**	7.578	6.684	15.790
à trous PCA (Object-based)	0.854	7.551	**7.033**	**12.556**

In visual, the spectral of à trous fusion method is better than the Mallat's fusion method (figure 8 (e),(g),(i)). Especially, the spectral information in region A is very obvious, that is because the region A in wavelet plane of à trous is very smoothness. However, the à trous algorithm is less suitable for extracting detail information of smooth region.

5 CONCLUSION AND DISCUSSION

The study proposed an object-based wavelet fusion frame. On the basis of analyzing image segmentation, wavelet transformation, and fusion rule, two object-based image fusion methods based on wavelet and PCA are researched. The wavelet transform is a popular fusion technique at present with the decomposition level and the fusion strategy which could be adjusted to preserve the image spectral and spatial information. The SRMMHR segmentation method is used to get segmented label image to guide the OBIF technique. The self-adjustable fusion rule with object energy could control the contribution of different components.

The fusion results showed that the object-based image fusion method performs better both in improving the spatial information and in preserving the spectral information than the pixel-based image fusion method. But the process time is longer because of the segmentation. Nevertheless, there are many forewords that require future investigation, including the analysis of the segmentation method, the effect of fusion rule to image fusion.

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