EVALUATION OF SATELLITE IMAGE FUSION USING WAVELET TRANSFORM

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ABSTRACT:

This paper addresses the principles, implementation and evaluation of wavelet transformation based image fusion. 2-D discrete wavelet transformation is presented concisely to facility the understanding of the wavelet based image fusion method. To best retain the quality of the input images, we propose a strategy that minimizes the necessary resampling operations to limit potential image quality deterioration. In the proposed fusion approach, the wavelet coefficients for the fused images are selected based on the suggested maximum magnitude criterion. To evaluate the outcome images, other popular fusion methods including principal component transformation, Brovey and multiplicative transformation approaches are applied to the same images and the results are compared to the ones from the wavelet based approach. Fusion results are evaluated both visually and numerically. A quality matrix is calculated based on the correlation coefficients between the fused image and the original image. It is shown that this quality measure can indicate the information content of the fused image comparing to the input panchromatic and multispectral images. Our results clearly suggest that the wavelet based fusion can yield superior properties to other existing methods in terms of both spatial and spectral resolutions, and their visual appearance. This study is carried out using multiple images over the Davis-Purdue Agricultural Center (DPAC) and its vicinity with both urban and rural features. Images used include QuickBird panchromatic band (0.7 m) and multispectral bands (2.7m), and Ikonos panchromatic (1 m) and multispectral bands (4 m).

1. INTRODUCTION

Image fusion, in general, can be described as a process of producing a single image from two or more images that are collected from the same or different sensors. The objective of the fusion process is to keep maximum spectral information from the original multispectral image while increasing the spatial resolution (Chavez et al, 1991; Ranchin et al, 2003). Military, medical imaging, computer vision, robotic industry and remote sensing are some of the fields benefiting from the image fusion.

In the field of remote sensing, lower spatial resolution multispectral images need to be fused with higher resolution panchromatic images. The fusion techniques should ensure that all important spatial and spectral information in the input images is transferred into the fused image, without introducing artifacts or inconsistencies, which may damage the quality of the fused image and distract or mislead the human observer. Furthermore, in the fused image irrelevant features and noise should be suppressed to a maximum extent. Image fusion can be performed at pixel, feature and decision levels according to the stage at which the fusion takes place (Pohl and van Genderen, 1998).

In this study, a pixel level multispectral image fusion process using wavelet transform approach is performed. The fusion process is implemented to two categories: images collected by the same sensors at the same time, and images collected by different sensors. For the same sensors, a QuickBird panchromatic image is fused with QuickBird multispectral images. For the different sensors, a QuickBird panchromatic image is fused with Ikonos multispectral images. Haar and Daubechies (DB) wavelets are used in this study. For comparison purpose, the same images are also fused using Principle Component Analysis (PCA), Brovey and Multiplicative Transformation methods to evaluate the proposed wavelet transformation approach. Finally, a quantitative evaluation criterion is proposed to evaluate the quality of the fusion outcome.

2. WAVELETS AND WAVELET TRANSFORM

In this paper, 2-D Discrete Wavelet Transform (DWT) is used for image fusion process. Wavelet transform is defined as the sum over all time of the signal multiplied by scaled, shifted version of the mother wavelet $\psi(t)$. Similar to the Fourier analysis that breaks a signal into different sine waves of different frequencies, wavelet transform decomposes a signal into the scaled and/or shifted versions of the mother wavelet (Misiti, 2002).

In DWT, instead of calculating wavelet coefficients at every possible scale, the scales and shifts are usually based on power of two. If we have a mother wavelet,

$$\psi_{m,n}(t) = 2^{-m/2}\psi\left(2^{-m}t - n\right) \tag{1}$$

A signal *f(t)* can be expressed by wavelets as

$$f(t) = \sum_{m,n} c_{m,n}\psi_{m,n}(t) \tag{2}$$

where m and n are integers (Nikolov et al, 2001). Here, $\psi_{m,n}(t)$ is the dilated and/or translated version of the mother wavelet ψ. To implement an iterative wavelet transform $a_{m,n}$ coefficients are needed. These coefficients denote the approximation of f at each scale. For example $a_{m,n}$ and $a_{m-1,n}$

designate the approximations at the resolution of 2^m and the coarser resolution 2^{m-1}. $c_{m,n}$ also denotes the difference between one approximation and the other. To calculate $a_{m,n}$ and $c_{m,n}$ coefficients, a scaling function is necessary. Then, the convolution of scaling function and the signal is implemented at every scale using a low pass FIR (Finite Impulse Response) filter h_n to calculate $a_{m,n}$ coefficients (Nikolov et al, 2001). This process can be designated with the following equation (Nikolov et al, 2001).

$$a_{m,n} = \sum_k h_{2n-k} a_{m-1,k} \qquad (3)$$

Similarly, by using a related high pass FIR filter g_n the $c_{m,n}$ coefficients are calculated using the following equation (Nikolov et al, 2001).

$$c_{m,n} = \sum_k g_{2n-k} a_{m-1,k} \qquad (4)$$

For 2-D DWT, it is just necessary to separately filter and downsample the image in the horizontal and vertical directions (Nikolov et al, 2001). By doing this, the spatial resolution is halved at each level by subsampling the image by a factor two. Each image provides four sub-images at each resolution level corresponding to one approximation image (low spatial resolution) and three detail (horizontal, vertical and diagonal) images (Chibani and Houacine, 2002). The same input image can be obtained by inverse DWT using calculated wavelet coefficients.

3. IMAGE FUSION ALGORITHM

3.1. Preprocessing of input images

In image fusion, the first step is to prepare the input images for the fusion process. This includes registration and resampling of the input images (Zhou, 1998). Registration is to align corresponding pixels in the input images. This is usually done by geo-referencing the images to a map projection such as UTM (Universal Transverse Mercator). If the images are from the same sensors and taken at the same time, they are usually already co-registered and can be directly used for fusion processing. However, if the images are from different sensors, and even if they are georeferenced by the image vendors, a registration process is likely still necessary to ensure that pixels in the input images exactly represent the same location on the ground.

Image registration can be performed with or without ground control. The most accurate way is to rectify the images using ground control points. However, in most cases, it is not possible to find ground control points in the input images. In such situations, taking the panchromatic image, which has a better spatial resolution, as the reference image and registering the multispectral images with respect to the panchromatic one can be a good solution to refine the rectified multispectral images.

Image fusion essentially occurs when the involved images or their transformation have the same spatial resolution. In the selected wavelet decomposition, the dimension of the newly decomposed image becomes half the size of the image at the previous level (Chibani and Houacine, 2002). Therefore, another important task in the preparation phase is to make the proportion between the pixel spacing of the panchromatic and multispectral images to be a power of two. The panchromatic and multispectral images of the same sensors (i.e. QuickBird, SPOT and Ikonos panchromatic and multispectral images respectively) may inherently meet this requirement. For example, the proportion between the pixel sizes of the panchromatic and multispectral images is 2^2 for QuickBird images (0.7m. versus 2.8m. for panchromatic and multispectral bands respectively). For this reason, no resampling is needed for these images. Their pixel sizes will be the same if one-level and three-level discrete wavelet decomposition are performed to these images respectively. If the pixel size of the input images does not have the 2^n multiplier relationship, resampling is needed.

However, resampling will deteriorates the quality and structure of the image involved. For this reason, it is expected that the resampling should be performed at minimum extent. (Du et al, 2003) propose an algorithm to find the minimum resampling needed. According to this algorithm, a coefficient S that makes the pixel sizes (P_A, P_B) of two images (A and B) equal is determined using the equation $P_A = SP_B$. Then, another number S_n, which is the nearest number to S that is the power of two, is found. Finally, the image A, which has a larger pixel size, is resampled to have a pixel size of S_n*P_B. This approach ensures that the resampled image now has a pixel spacing that the proportion between the P_B and resampled image is the power of two. It also ensures that the $(S-S_n)$ is the minimum number that meets this requirement. This resampling approach is used in our study.

3.2 Implementing wavelet transform

Wavelet transform based image fusion involves three steps; forward transform, coefficient combination and backward transform. In the forward transform, two or more registered input images are calculated to get their wavelet coefficients. These coefficients respectively represent the approximation, horizontal, vertical and diagonal components of the input images (Hill et al, 2002). Figure 1 below illustrates a 2-D forward DWT process (Misiti, 2002).

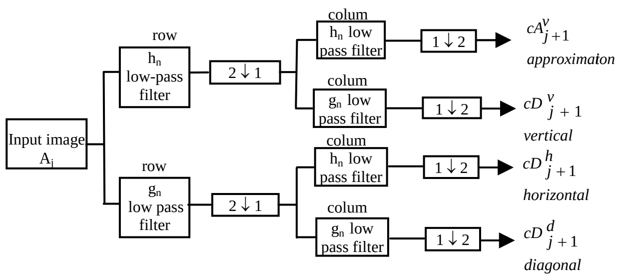


Figure 1. 2-D forward DWT to get approximation, vertical, horizontal and diagonal wavelet coefficients

The same process needs to be applied to all input images one by one. Then, these wavelet coefficients from the different input images are combined according to certain fusion rules to get fused wavelet coefficients.

3.3 Fusion Rules

This is where the fusion essentially occurs. The wavelet transform coefficients obtained from the input images need to be combined to form a new set of coefficients to be used for backward transform. There are various fusion rules to form the fused wavelet coefficients matrix using the coefficients of the input images. In this study, taking the largest absolute values of the corresponding wavelet coefficients among input images is chosen as the basic fusion rule.

After selecting the new fused wavelet coefficients according to a fusion rule, an inverse wavelet transform is done to construct the fused image.

4. TEST DATA

Two types of tests are designed. First, multispectral QuickBird images over the Davis-Purdue Agricultural Center (DPAC) are fused with the QuickBird panchromatic image. The second test is to fuse images taken from different sensors. A QuickBird panchromatic image over DPAC area is fused with Ikonos multispectral images. The properties of the images used in this study are given in Table 1.

The objective of fusing QuickBird and Ikonos images is to inspect the effects of different sensors on the fusion process such as different acquisition time, the image registration and alignment problems possibly caused by different platform attitudes, scales and projections. The principles of the fusion process algorithm are described in the following section.

Satellite	QuickBird		Ikonos	
Image	Pan	XS	Pan	XS
# Bands	1	4	1	4
XS Band #	Blue: 1; Green: 2; Red: 3;Near infrared: 4			
# bits	11	11	11	11
CE90% (m)	23	23	25.4	25.4
RMSE (m)	14	14	11.8	11.8
Collection date	May 3, 2002		April 16, 2002	
Resolution (m)	0.7	2.8	1	4
Used Size in Fusion (row x col)	2600x 2600	650x 650	Not used	650x 650
Projection	UTM WGS 84			

CE: circular error; RMSE: root mean square error; XS: multi spectral

Table 1. Properties of test images

5. RESULTS AND EVALUATION

5.1 Fusion of QuickBird images

Since both images are taken at the same time and from the same sensor, no registration or rectification is needed. The resolutions of the multispectral image and the panchromatic one are 2.8 m. and 0.7 m respectively. The multispectral image, which has four bands, is separated into four individual bands. As shown in Figure 3, one-level wavelet transform is applied to the individual bands of the multispectral image to get their wavelet coefficients. Since the pixel spacing of the panchromatic image is four times less than the multispectral ones, three-level wavelet decomposition is necessary for the panchromatic image so that its pixel spacing becomes the same as the multispectral images.

The next step is to choose a fusion rule to determine the appropriate wavelet coefficients for the fused image. The basic requirement is to retain the features and realistic colors, respectively from the panchromatic and multispectral images. Since wavelet coefficients with large magnitude contain the information about the salient features of the images such as edges and lines (Li, 1994), taking the largest absolute values of the corresponding wavelet coefficients is chosen as the basic fusion rule. Therefore, the horizontal, vertical and diagonal detail coefficients of the one-level decomposed multispectral bands and three-level decomposed panchromatic image (they have the same pixel spacing and image dimension at this level) are matched pixel by pixel and the largest absolute values are taken to be the detail coefficients of the fused image.

However, in order to retain color information in the multispectral image, the approximation coefficients are treated differently. In fact, the approximation coefficients of multispectral bands are kept unchanged in the fusion process.

After obtaining the new approximation, horizontal, vertical and diagonal coefficients for the fused image, three-level inverse wavelet decomposition is performed. As the result, a multispectral image with 0.7m spatial resolution is obtained. This process is repeated for each individual multispectral band. Finally, four fused new image is concatenated to form a new four-band fused image. This process is illustrated below in Figure 2 and the fused image is given in Figure 3.

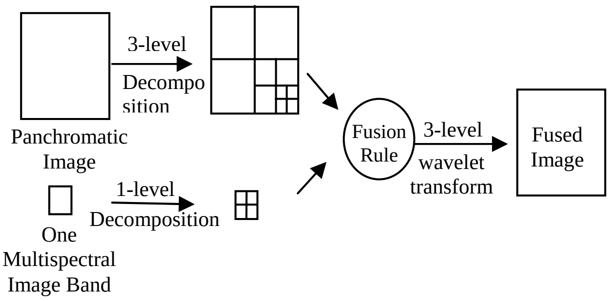
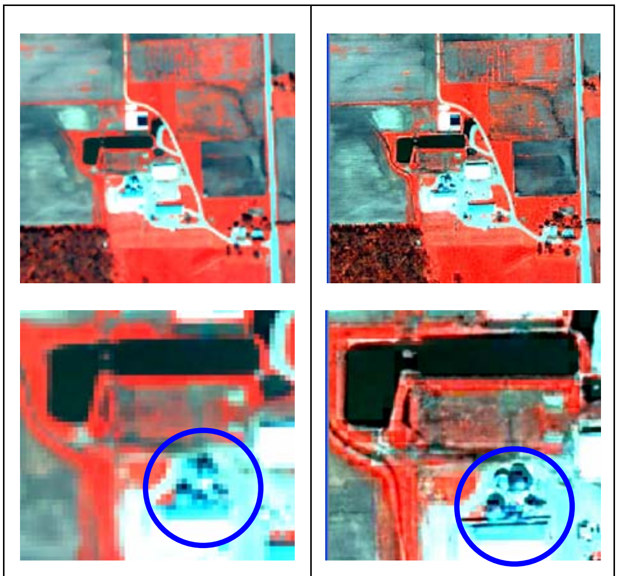


Figure 2. Handling different resolutions in wavelet-based fusion



Original Multispectral Image (QB)	Fused Image

Figure 3. Fusion of QuickBird pan and multispectral images

5.2. Fusion of QuickBird and Ikonos images

This task needs registration and resampling prior fusion as discussed earlier. QuickBird panchromatic image is taken as the reference to which the Ikonos multispectral images are registered. As for resampling, the Ikonos multispectral images are resampled from 4m to 2.8m pixel size, which is 2^2 times 0.7m of the QuickBird panchromatic image resolution and is the closest number to 4m. In this way, the necessary resampling is limited to the minimum and the quality of the original image is best retained in this process. After this preprocessing, procedures outlined in Figure 2 are followed to conduct the fusion process. The outcome of this process is four multispectral images with a spatial resolution of 0.7m.

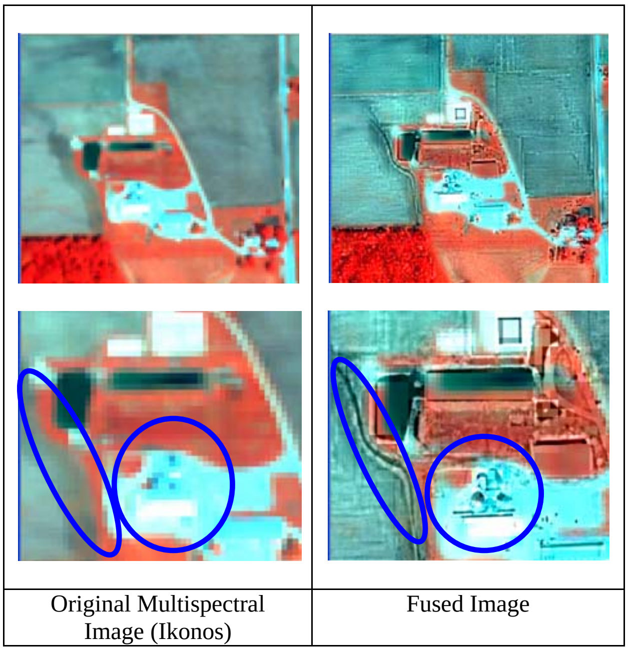


Figure 4. Fusion of QuickBird pan and Ikonos multispectral images

5.3. Visual and Quantitative Evaluation

5.3.1 Visual Evaluation

For visual evaluation, two approaches are used. First, the proposed fusion algorithm is evaluated in terms of spatial and spectral improvements. It is clearly seen from the pictures in Figure 3 and 4 that the spatial resolutions of the images after the fusion are improved. In the original QuickBird and Ikonos images, it is very difficult to discern some physical features like small buildings. For example, in both multispectral images there are some circular objects that are very difficult to perceive whether they are buildings or not. In Ikonos, it becomes even more difficult, nearly impossible, to see these plants (the blue circled area).

However, in both fused images, it becomes clear that there are some circular man-made features, which are most likely silos that farmers use to store their crops. Also, there is a small road or water way that can be apparently seen in the fused images (blue oval), which are not perceivable in the original Ikonos image. The fused images also keep the original colors that means that the spectral content of the images are carried to the fused ones. Therefore, the fused images will significantly improve the image classification results.

Secondly, as a comparison, the same images are fused also using PCA, Brovey and Multiplicative image fusion techniques using Erdas Imagine 8.6. Figure 5 below presents the fusion results of QuickBird Pan and Multispectral images. It is seen that these fusion methods also improve the spatial resolution. But, the colors of the features in the fused images are changed. This color distortion effect is the largest in Brovey method. Among these three methods, multiplicative transformation gives the best result in terms of color conservation. However, wavelet transform approach is superior to these three results, as the colors of the features in original multispectral images are nearly the same in the fused image.

Finally, the images are fused using DB wavelet. As seen from the Figure 6, the DB wavelet gives a better spatial resolution when compared to the results from Haar wavelet. This implies that the selection of different wavelets may affect the fusion results. In this paper, for its simplicity, fusion results of Haar wavelet are used for algorithmic description and the comparisons with the results of other fusion methods in the visual evaluation part. All correlation coefficients used in quantitative evaluation part are also calculated using the fused images with Haar wavelet.

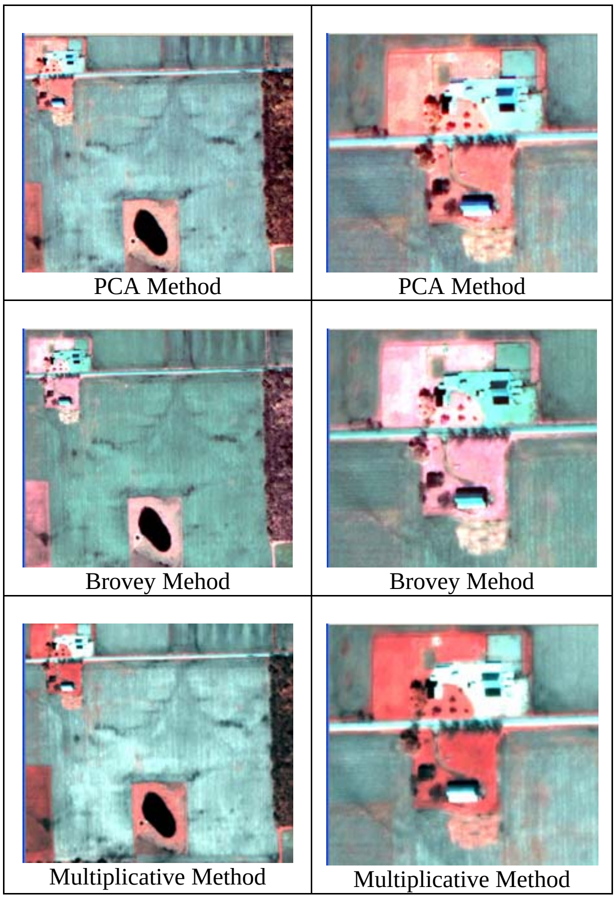


Figure 5. Fusion of QuickBird pan and multispectral images using PCA, Brovey and Multiplicative fusion methods.

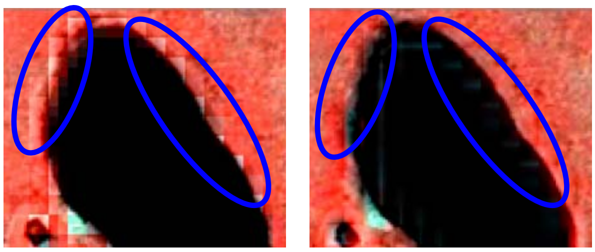


Figure 6. Fusion using Haar (left) and DB 2.2 (right) wavelets.

5.3.2. Quantitative Evaluation

In general, a good fusion approach should retain the maximum spatial and spectral information from the original images and should not damage the internal relationship among the original bands. Based on these three criteria, correlation coefficients are used to quantitatively evaluate the image fusion results.

In Table 2, the correlation coefficients between the original panchromatic image and the fused images (QB Pan + QB XS) are given as a quality measure. As is shown, the correlation coefficients are getting larger after fusion, which implies that the fused image gains information from the original panchromatic image. The amount of increase varies from 7% (band 4, near infrared) to 12% (band 1, blue), with the blue band having the most gain from the panchromatic image.

Table 3 presents the correlation coefficients of the fused images with their corresponding original images. The higher the value, the more similar the fused image to the corresponding original image, which in turn indicates a good spectral information retain in the fused results. As shown in the table, all bands except the blue one have a high correlation over 0.93 to their corresponding original images. The fused blue band has the lowest correlation of 0.85 to the original blue image. This property is consistent with the above analysis as the blue band is most affected in the fusion process by gaining the most spatial information from the panchromatic image.

Table 4 presents the correlations among the QuickBird multispectral bands before and after fusion. A good fusion approach should not considerably change the correlation in the corresponding bands. As shown in Table 4, the correlation among all bands but band 4 is subject to a minor change after fusion. The magnitude of largest correlation change is 0.02, which is only about 2% of the original correlation. However, the behavior of band 4 (near infrared) presents different properties. For both before and after fusion, band 4 has a very small correlation with all other multispectral bands, with the maximum correlation being only 0.19. Although the magnitude of correlation change is still very small (with the largest being only 0.07), their relative rate can be large (over 200%). This implies that the near infrared image is the most affected image in terms of the internal relationship with other bands in the fusion process.

Table 5 shows the correlation coefficients between each original multispectral band and the fused ones of QuickBird image computed for PCA, Brovey, Multiplicative and the Wavelet transform methods. The larger the correlation coefficient, the more spectral content is retained from the original multispectral images. Results in Table shows that the wavelet transform approach keeps over 90% of the spectral content of all original multispectral bands except band-1 (blue band). Among the tested methods, wavelet based approach is the only one that keeps the most number of bands (3) having a correlation above 90%. Further examination on Table 5 shows the magnitudes of correlation change from band to band, that suggests that the performance of fusion methods is band selective. A reasonable expectation on a good fusion method is that they have similar properties across the bands involved. Results in Table 5 show that the Brovey method results in the largest range (max – min), whereas the Multiplicative and wavelet methods yield similarly small ranges (0.04 and 0.07) across the bands. All the above analysis suggests that the wavelet based fusion approach provides overall the best results in the methods used in our study.

		XS1	XS2	XS3	XS4
QB Pan	before	0.6901	0.7444	0.6753	0.6138
	after	0.7732	0.8063	0.7352	0.6572

Table 2. Correlation coefficients between the original QB pan and multispectral bands before and after fusion

XS1	XS2	XS3	XS4
0.8501	0.9323	0.9516	0.9374

Table 3. Correlation coefficients between the corresponding original and fused QB multispectral images

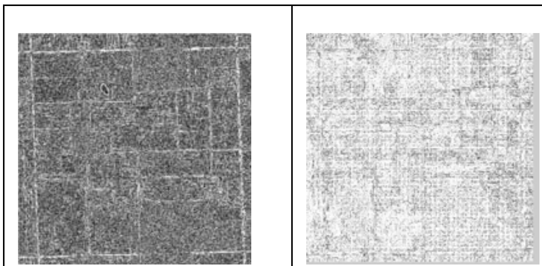
		XS1	XS2	XS3	XS4
XS1	Before	1	0.9893	0.9647	0.0905
	After	1	0.9671	0.9409	0.1645
XS2	Before	0.9893	1	0.9723	0.1596
	After	0.9671	1	0.9740	0.1889
XS3	Before	0.9647	0.9723	1	0.0193
	After	0.9409	0.9740	1	0.0593
XS4	Before	0.0905	0.1596	0.0193	1
	After	0.1645	0.1889	0.0593	1

Table 4. Correlation coefficients among the QB multispectral bands before and after fusion

	Band1	Band2	Band3	Band4
PCA	0.7743	0.7743	0.7907	0.9621
Brovey	0.8766	0.6302	-	0.4683
Multiplicative	0.8539	0.8777	0.8958	0.861
Wavelet	0.8501	0.9323	0.9516	0.9374

Table 5. Correlation coefficients between original and fused QB multispectral bands for different fusion methods

Despite the above studies, one correlation coefficient can only represent the overall quality of the fusion results. In fact, fusion quality can be higher for certain features than others since they can give a better response to the fusion algorithm. For this reason, we suggest to calculate the correlation coefficient for a small window instead of the entire image. A window that has a predefined size w (i.e. w = 3 for a 3X3 window) is taken and the correlation coefficient is calculated for the two images that falls in this window. In this way, the texture contents at higher levels of details in the before- and after- fused images can be directly compared. This process is started from the upper left corner of the image and continued until whole image is covered. At the end of this process, a quality matrix made of the correlation coefficients is created. Brighter places in this quality matrix suggest better fusion quality than darker places. Figure 7 shows the quality matrices represented as a grey level image.



Pan vs. XS Band-1 | Pan vs. Fused XS Band-1

Figure 7. Quality matrices before (left) and after (right) fusion calculated for QB images using 3 x 3 window.

Image to the left side is the quality matrix that is made up of the correlation coefficients calculated for QuickBird panchromatic band and the original multispectral band-1. The image to the right shows the corresponding quality matrix for the QuickBird panchromatic band and the fused multispectral band-1. By doing this, the responses of the some geographic or physical features to the fusion algorithm can be detected. For example the image on the left side is darker than the one on the right side. This implies that the image on the right side is made up of larger correlation coefficients. This result is proven from the Table 2. The over all correlation coefficient for original multispectral band-1 and the fused band-1 is 0.69 and 0.77 respectively.

6. CONCLUSIONS

It is demonstrated that, when different sensors are used, the image co-registration becomes important. Even if two input images have the same projection and datum, they are generated independently with different processing steps, sensor models, trajectory data and ground truth. It is observed that the same ground features in the Ikonos and QuickBird images have apparent mis-registration. For this reason, while preparing the images for the fusion process, careful attention must be given to make sure that the same pixels in the two images represent the same geographic position in the field.

For different sensors, the temporal difference between the acquisitions of the two images also causes some problems. If a feature in one of the images is not exist anymore, or changed partially, this will result in poor quality in the fused image.

In general, a good fusion approach should retain the maximum spatial and spectral information from the original images and should not damage the internal relationship among the original bands. Based on these three criteria, correlation coefficients are used to quantitatively evaluate the image fusion results. The higher correlation coefficients between the panchromatic image and the fused image imply the improvement in spatial content when compared to the correlation coefficient calculated for panchromatic and original multispectral images. Likewise, a fused image should have high correlation to the corresponding original multispectral image to retain spectral information. In addition, the fused multispectral images should preserve the same correlation properties as the ones of the original multispectral images. Therefore, their difference needs to be small. Fusion quality can also be evaluated locally, where correlation coefficients are calculated within a neighborhood of a pixel. In this way, the proposed quality measure can help understand the responses of different geographic features to the fusion algorithm. It is shown that the fused image have over 0.9 correlation except band 1 (blue band) with the original multispectral images, and 0.7 correlation with the panchromatic image. It is the highest comparing the tested exiting fusion methods: PCA, Brovey and multiplicative. This reflects a good retaining of both spatial and spectral information during the fusion process.

This study is a successful experience with the wavelet transform based fusion approach. It is shown that proposed wavelet transform approach improves the spatial resolution of a multispectral image while it also preserves much portion of the spectral component of the image. Some features that can not be perceived in the original multispectral images are discernable in the fused ones. By properly designing the rules in combining the wavelet transform coefficients, color distortion can be minimized. Fusion results preserve the same color appearance as the original multispectral images, even when images collected by different sensors are involved.

Finally, different wavelets tend to yield different fusion quality. This is observed when comparing the fusion results obtained from Haar and Daubechies wavelets. It is shown Haar wavelet may cause the effect of squared feature boundary, where Daubechies wavelet presents a smooth and natural transition. This topic along with further formulation of fusion quality will be our future effort of study.

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