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Wavelet-based hyperspectral and multispectral image fusion

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ABSTRACT

Different research groups have recently studied the concept of wavelet image fusion between panchromatic and multispectral images using different approaches. In this paper, a new approach using the wavelet based method for data fusion between hyperspectral and multispectral images is presented. Using this wavelet concept of hyperspectral and multispectral data fusion, we performed image fusion between two spectral levels of a hyperspectral image and one band of multispectral image. The reconstructed image has a root mean square error (RMSE) of 2.8 per pixel and a signal-to-noise ratio (SNR) of 36 dB. We achieved our goal of creating a composite image that has the same spectral resolution as the hyperspectral image and the same spatial resolution as the multispectral image with minimum artifacts.

Keywords: Hyperspectral, multispectral, wavelet, image fusion, data fusion

1. INTRODUCTION

Hyperspectral and multispectral imaging systems are widely used in Earth observing systems and regional applications. A Hyperspectral imaging system provides detailed spectral information that enables the observer to detect and classify a pixel based on its spectral characteristics. However, in many cases, the spatial resolution of these systems is lower than a multispectral imaging system that has less spectral channels [1].

NASA's newly launched EO-1 spacecraft will provide researchers with space-based Earth observations with unique spatial and spectral characteristics. Hyperion is one of the key instruments on board this spacecraft capable of resolving 220 spectral bands (from 0.4 to 2.5 μm) with a 30-meter spatial resolution [2]. Although the spatial resolution of this instrument is better or equal to many conventional imaging systems such as Landsat, it is still less than the spatial resolution of SPOT 4 or Space Imaging's Ikonos. The SPOT 4 satellite carries two instruments, a high-resolution visible and infrared instrument and a vegetation instrument, that have 20 m pixel resolution in the multispectral mode [1]. Ikonos has 4 m spatial resolution for multispectral data. In many remote-sensing applications, it is imperative to maintain high spectral and spatial resolution [3]. Therefore, image fusion between hyperspectral and multispectral images becomes important to achieve such a goal.

2. IMAGE FUSION

Image fusion refers to a process that extracts redundant and complementary information from a set of input images and fuses it into a single and more complete image. The fused image should have more useful information content. The fusion of the two images can take place at the signal, pixel, or feature level [4]. In this paper, the problem of image fusion at the pixel level is being addressed.

One of the main issues in image fusion is image alignment, which refers to pixel-by-pixel alignment of the images. Another important issue is the dynamic range between the two hyperspectral and multispectral images. Since different sensors provide these images, the dynamic range of the two images must be rescaled to match one another. Different research groups have recently studied the concept of wavelet image fusion between panchromatic and multispectral images from different approaches. For details on their work interested readers are referred to [5], [6]. In the concept of hyperspectral and multispectral presented in this paper, image fusion will occur between two spectral levels of hyperspectral and one band of multispectral image. The reconstructed image will have the same spatial resolution as the multispectral image and the same spectral resolution as the hyperspectral image as shown in figure 1

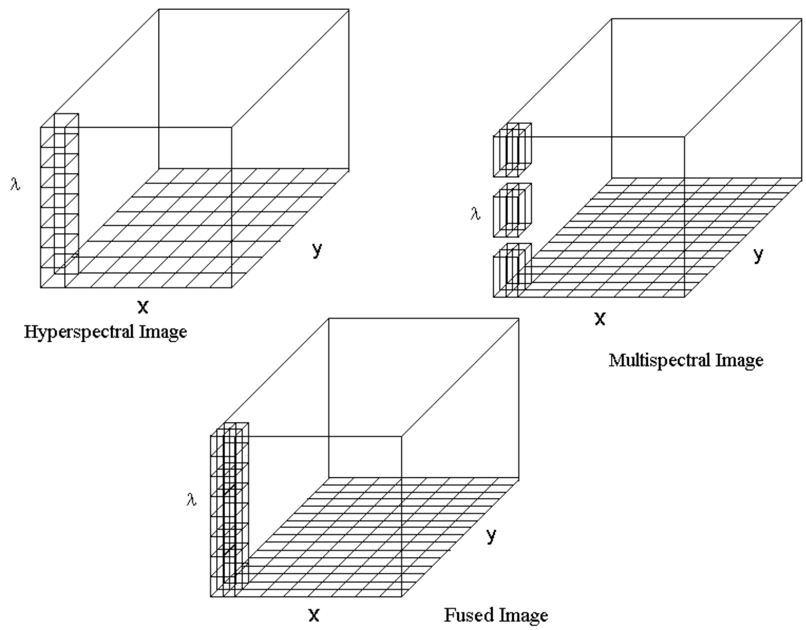

Figure 1

2.1 Wavelet-based image fusion

Wavelets are translation and dilation operators generated from a unique function ψ that decomposes a signal into a family of functions ψ_s. These operators can be considered as low-pass and high-pass filters. The low-pass filter is a moving average and the high-pass filter is the moving difference [7]. The wavelet transform of a two dimensional image is shown in figure 2. As shown in this figure the original image has been decomposed in to different types of details and levels. A more detailed discussion on wavelet based image processing is provided in [8], [9], and [10].

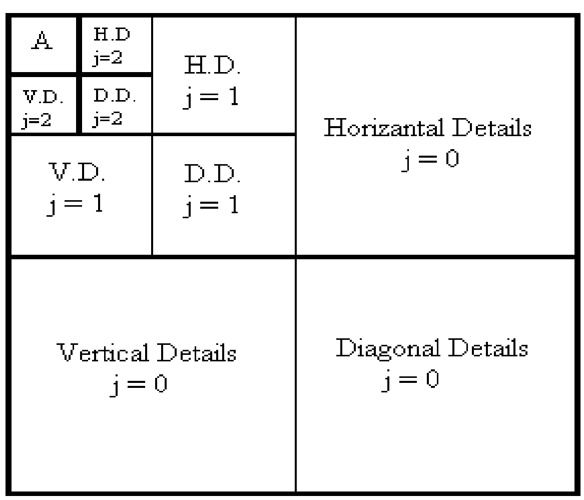

Figure 2: Detailed wavelet coefficients at different levels

The wavelet based image fusion will be applied to a two-dimensional hyperspectral test image at each level as shown in figure 3. In this method pixel "a" will be fused with pixels "g, i, j, and k". In order to fuse one pixel with 4 pixels, pixel "a" will be inversed wavelet transformed to obtain coefficients "a1, a2, a3, and a4". An architecture that is equally efficient at computing both the discrete wavelet transform (DWT) and the inverse discrete wavelet transform (IDWT) has been described in the literature [11].

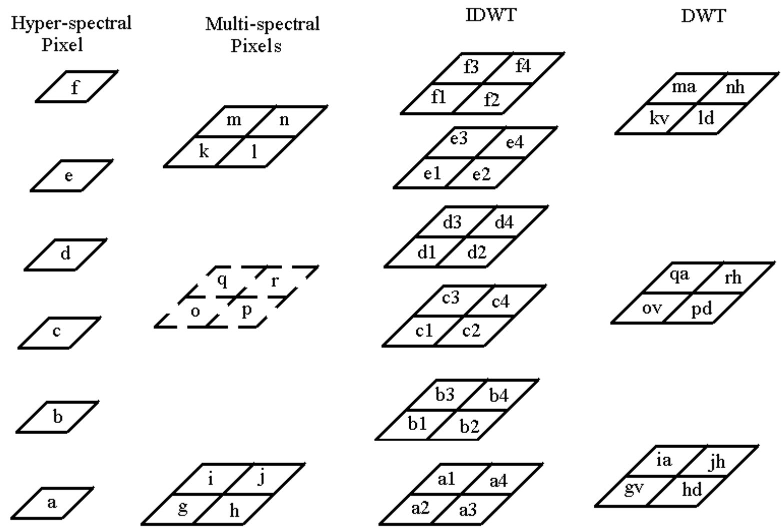

Figure 3

These coefficients then will be added to four wavelet transform coefficients gv, hd, ia, and jh that correspond to approximation and detail coefficients corresponding to "g, h, i, and j" of the multispectral test image as shown in figure 4. In the next spectral level pixel "b" will be fused with "g, h, i, and j" the same way that pixel "a" was fused. The reason is both pixel "a" and "b" in the hyperspectral data fall in to the same wavelength range as pixels "g, h, i, and j" in the multispectral band.

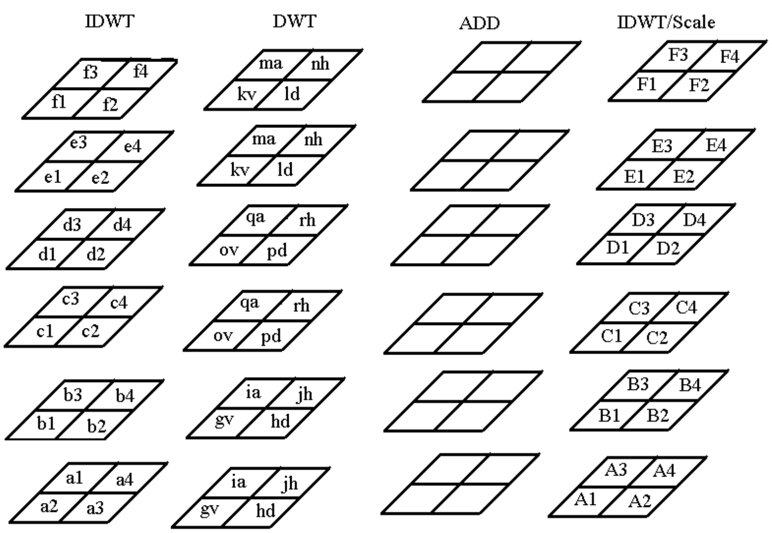

Figure 4

The process continues by fusing pixel "c" in hyperspectral level with pixels "o, p, q, and r" in the multispectral band. Pixels "o, p, q, and r" do not exist in the multispectral test image and are considered as the missing data. The values of these pixels are interpolated using the existing data from the existing multispectral test image bands and the corresponding hyperspectral test image. For instance, pixel "o "is the average between pixels "g" and "k" in the multispectral band and "c" and "d" in the corresponding hyperspectral level of test images. After finding the fused coefficients, each block of 4 coefficients will be inversed wavelet transformed and rescaled to produce 4 pixels in the corresponding level of the reconstructed image. The process continues until all the pixels in hyperspectral test image will become fused to their corresponding pixels in the multispectral test image.

3. RESULTS

The above algorithm was applied to a hyperspectral test image of the size 64x64 with 28 spectral levels and a multispectral test image of the size 128x128 with 7 spectral bands. Both test images were constructed from a hyperspectral image with 128x128 resolution and 28 spectral levels. Unlike other techniques that rely on human perception, this approach provides an effective way of comparing the reconstructed image with a reference image. Each pixel in the hyperspectral test image is the average of 4 pixels in the original image, and each spectral band in the multispectral test image is the average of 2 levels in the original image. Instead of having 14 bands, the multispectral test image has only 7 bands. The other 7 bands were discarded to make the problem more realistic. The reconstructed image has 128x128 resolution with 28 spectral levels, the same as the original hyperspectral image as shown in figure 5.

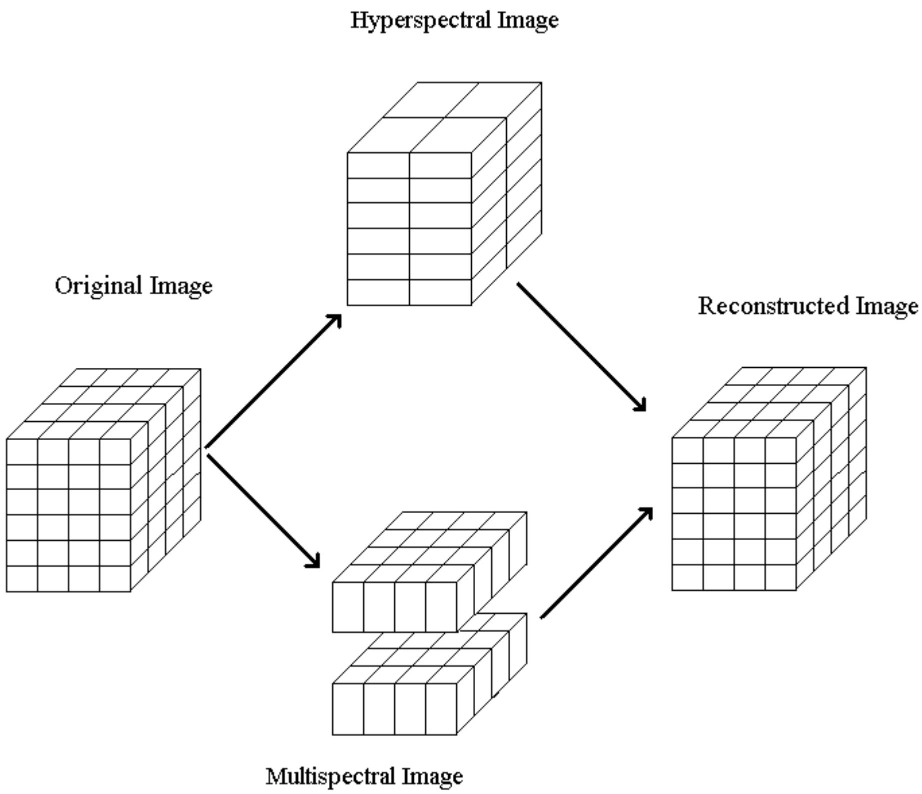

Figure 5

The original and reconstructed images for levels 9, 10 and 11 along with the difference between original and reconstructed images for the above mentioned levels are shown in figure 6. Since level 11 was reconstructed using an averaging scheme, it contains more artifacts than levels 9 and 10.

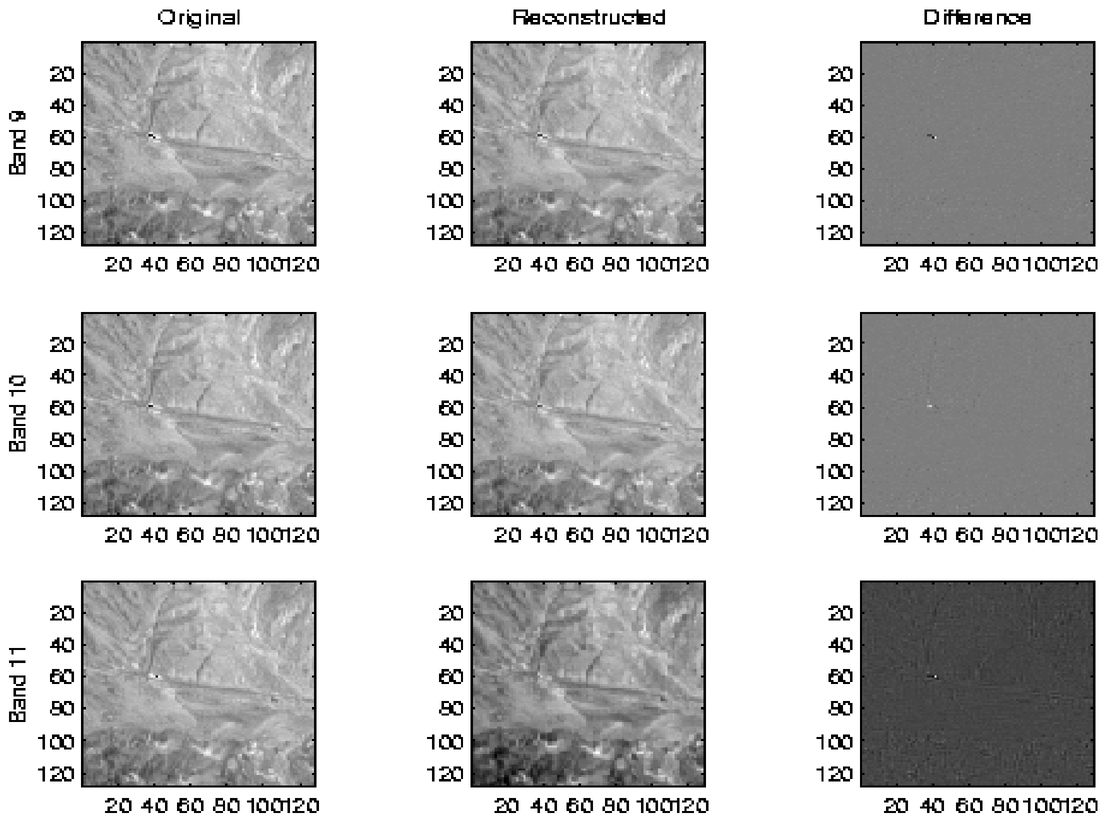

Figure 6

The spectral variation of an original pixel is depicted in figure 7. It is shown that most of the error between the original and reconstructed spectral information is coming form the averaged data. The root mean square error (RMSE) and signal to noise ratio (SNR) between the reconstructed and the original image was calculated using the following equations:

$$RMSE = \frac{1}{N^2}\sqrt{\sum_i \sum_j (X_{i,j} - Y_{i,j})^2}$$

where X is the original image and Y is the reconstructed image. The RMSE had the value of 2.487 per pixel and the SNR was 36.448 dB.

$$SNR = 10 * \log(\frac{\sum_i \sum_j (X_{i,j} - Y_{i,j})^2}{\sum_i \sum_j X_{i,j}{}^2})$$

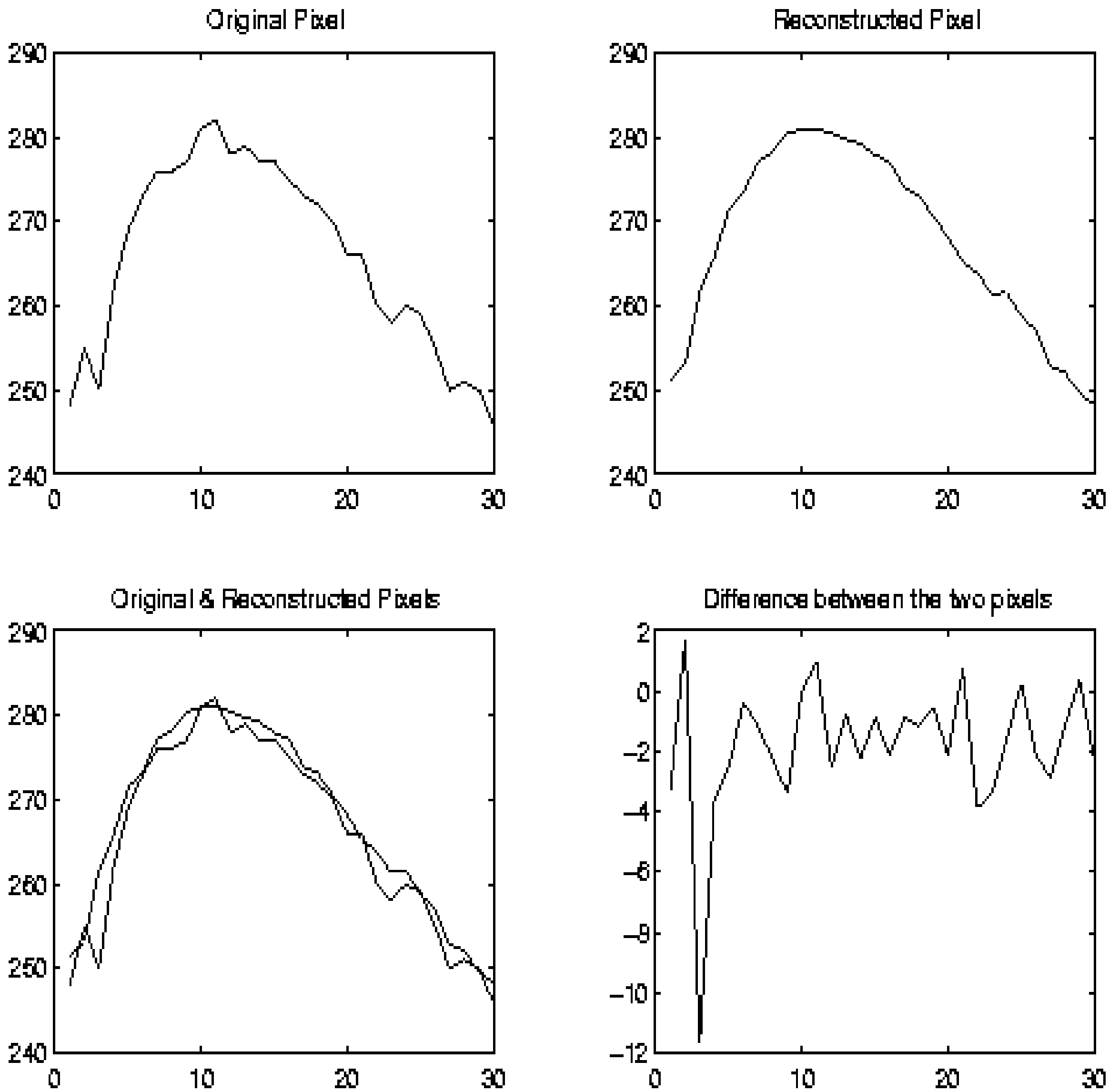

Figure 7

4. CONCLUSIONS

A new wavelet based method for data fusion between hyperspectral and multispectral images was studied. Based on the presented results it is shown that fusion between multispectral and hyperspectral images using wavelets produces high-spectral and spatial images with minimum artifacts. Although the above method only used two input images for fusion, the algorithm can easily be extended to accommodate more input images. It is worthy to note that by using more advanced techniques to interpolate the missing data corresponding to the multispectral bands, achieving higher SNR and lower RMSE is highly possible.

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