Hybrid Compression of Hyperspectral Images with Resizing

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Abstract: In this paper, we propose a hybrid compression method with resizing. The proposed method is based on the 3-D SPIHT algorithm. In the proposed algorithm, we first reduce 3-D hyperspectral images using a 3-D interpolation algorithm and encode the reduced 3-D images using the 3-D SPIHT algorithm. At the decoder side, encoded data is first decoded using the 3-D SPIHT algorithm and the reconstructed 3-D images are enlarged to the original image size. However, it is found that image reduction puts a limit on reconstructed image quality. In order to address this problem, we propose a hybrid compression method, which utilizes rescaling and difference coding. Experimental results show that the proposed algorithm provides improved performance compared to the conventional 3-D SPIHT algorithm at low bit rates and is comparable to the conventional 3-D SPIHT algorithm at higher bit rates.

Key-Words: - hybrid compression, difference coding, resizing, 3D-SPIHT.

1 Introduction

Recent development of sensor technology produces hyperspectral images which contain hundreds of spectral bands. In general, such hyperspectral images are very large in size and need to be compressed to store for storage or transfer through networks in many cases. Although low-bit rate coding of hyperspectral images will be useful for searching images in storage or distributing images through networks, the performance of the coding schemes designed for low bit rates should not be compromised at high bit rates. Recently, a low-bit rate coding algorithm for hyperspectral images has been proposed, which first reduces images prior to encoding [1]. Although the coding method provides better compression efficiency at low bit rates, it is found that the image reduction restricts reconstructed image quality. In other words, although the compression method with image reduction provides better performance at low bit rates, the image quality at higher bit rates is inferior to that of the conventional coding method without image resizing.

In this paper, we propose a hybrid compression method which utilizes resizing and difference coding, based on the 3-D SPIHT algorithm. Experimental results show that the proposed method outperforms the conventional 3-D SPIHT algorithm at low bit rates and provides comparable performance at high bit rates.

2 Image Resizing and 3-D SPIHT

First, we briefly review 3-dimensional interpolation and the SPIHT algorithm. Then, we provide a brief summary of the hyperspectral image compression method [1] which first applies resizing and then encodes the reduced images.

2.1 Image resizing

Interpolation is a basic operation in image processing and is routinely used in image resizing. A number of interpolation algorithms have been proposed, and there are significant differences in complexity and performance. A typical procedure for interpolation is to fit digital data with a continuous signal and then resample the function at a desired sampling rate. The interpolation model that uses a B-spline kernel has a finite support and is widely used in various interpolation problems [5-6]. In the B-spline interpolation model, the signal is modeled as follows:

$$s(x) = \sum_{k \in \mathbb{Z}} c(k) \beta^n (x-k)$$

where $\beta^n(x)$ is the B-spline of degree n, which can be obtained from the (n+1)-fold convolution of the box function, and $c(k)$ is the B-spline coefficient computed from a given image $s(n)$. It is noted that and $c(k) \neq s(k)$ in the B-spline model if its degree is larger than two. B-spline coefficient $c(k)$ can be efficiently calculated with causal and anti-causal filter [5-6]. The B-splines spline kernel of degree 1, called bilinear interpolator, is widely used in hardware implementation of image interpolation due to its simple calculation and relatively good performance. However, the bilinear interpolation tends to yield undesirable artifact such as edge blurring. A higher degree interpolation provides a better quality image, but is computationally expensive. Sometimes, the B-spline interpolation models of high degrees may produce ringing effects in rapidly changed area, particularly around sharp edges. Thus, the cubic spline kernel is widely used since it provides high quality images with a reasonable computation cost. The cubic spline kernel $\beta^3(x)$ is given by

$$\beta^3(x) = \begin{cases} 2/3 - |x|^2 + |x|^3/2 & 0 \le |x| \le 1 \\ (2-|x|)^3/6 & 1 \le |x| \le 2 \\ 0 & otherwise \end{cases}$$

In general, interpolation is performed separately for 2-D or 3-D images. When interpolation is performed separately in each direction, the interpolated value is calculated in each direction using its four neighbor pixels of B-spline coefficients as follows:

$$y = c_0\beta^3(1+a) + c_1\beta^3(a) + c_2\beta^3(1-a) + c_3\beta^3(2-a)$$

In this paper, we use the cubic B-spline interpolation to reduce images prior to encoding. At the decoder size, we also use the cubic B-spline interpolation to enlarge the reconstructed images. It is also noted that interpolation is performed separately in each direction (two spatial directions and one spectral direction) for hyperspectral images.

2.1 3-D SPIHT (Set Partitioning In Hierarchical Trees)

Recently, image coding using the wavelet transform has attracted great attention [2-4, 7]. The coding method doesn't have the blocking effect of the DCT (Discrete Cosine Transform) at low bit rates**.** A number of compression methods using the wavelet transform have been proposed [2-3]. In particular, the SPIHT algorithm is widely used due to its performance and speed [3]. We will briefly describe the basic concepts of the SPIHT algorithm. Fig.1 shows the hierarchical pyramid structure of the wavelet transform. In the 2-D wavelet transform, each pixel has a direct descendant group of 2 x 2 adjacent pixels except the lowest and highest pyramid levels. The arrows are oriented from the parent node to its four direct descendants. Since most energy of an image is concentrated in low frequency regions, the parent node tends to have more energy than its descendant nodes**.** Furthermore, there is a spatial self-similarity between subbands. The SPIHT algorithm has been extended to 3 dimensional data and used to compress videos and hyperspectral images [4]. Fig. 3 shows hierarchical pyramid structure of the 3-D wavelet transform. In the 3-D wavelet transform, each pixel has a direct descendants group of 2×2×2 adjacent pixels except the highest and lowest pyramid levels. The 3-D wavelet transform is usually performed by three separate 1-D wavelet transform along rows, columns and spectral directions.

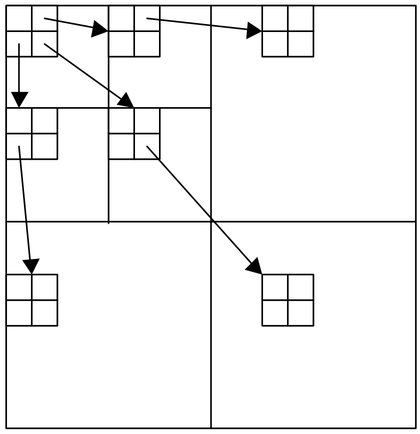

Fig. 1 Hierarchical pyramid structure of 2-D SPIHT.

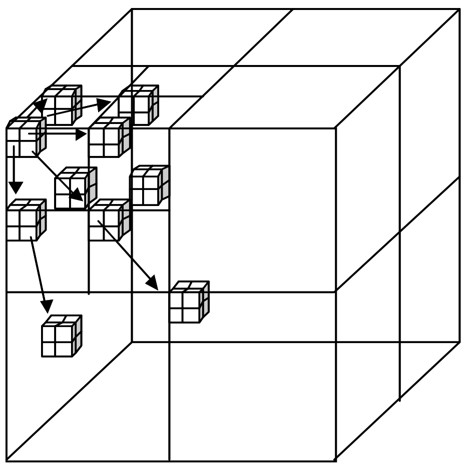

Fig.2 Hierarchical pyramid structure of 3-D SPIHT.

The SPIHT algorithm employs the successive approximation quantization (SAQ) [3], which gradually reduces distortion as more bits are added. After quantization process, entropy coding may be applied. In a typical SPIHT algorithm, the adaptive arithmetic coding is frequently used.

2.3 Compression of hyperspectral images with resizing

A low-bit rate coding of hyperspectral image would be useful for searching images in storage or distributing images through networks. Generally, the 3-D SPIHT algorithm is a good candidate for compression of hyperspectral image due to its good performance in compression efficiency and coding complexity. Recently, a low-bit rate coding algorithm for hyperspectral images has been proposed, which first reduces images prior to encoding [1]. Fig. 3 illustrates the compression algorithm with resizing. First, the original image cube (two-spatial dimensions and one spectral dimension) is reduced to a smaller image cube. The cubic spline interpolation is used in resizing. Then, the conventional 3-D SPIHT algorithm is used to compress the reduced image cube. At the decoder, the compressed data is first decoded and the decoded images are enlarged by the same factor. Although this compression method with image reduction provides better performance at low bit rates, the image quality is saturated as the bit-rate increases. Fig. 4 illustrates this quality saturation problem. In Fig. 4, the test images are reduced at two difference factors: 0.25 and 0.5. As can be seen, the compression method with image resizing provides better performance than the conventional compression method at low bit rates. It is noted that the 3-D SPIHT algorithm is used in Fig. 4. However, as the bit rate increases, the performance of the compression method with resizing becomes saturated. Adding more bits does not improve the performance. It is also noted that compression with a larger reduction (e.g., reduction ratio=0.25) provides better performance at low bit rates than the compression with a smaller reduction (e.g., reduction ratio=0.5). However, its performance is saturated sooner and the maximum performance is lower than that of the compression with a smaller reduction (e.g., reduction ratio=0.5). For instance, the maximum PSNR is about 25dB when the original image is reduced by 0.25 while the maximum PSNR is about 28dB when the original image reduced by 0.5. It is noted that PSNR is computed assuming the peak value is 4095.

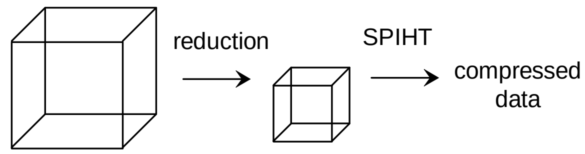

Fig.3 Encoding Process(Original size->down resizing -> 3-D wavelet and 3-D SPIHT).

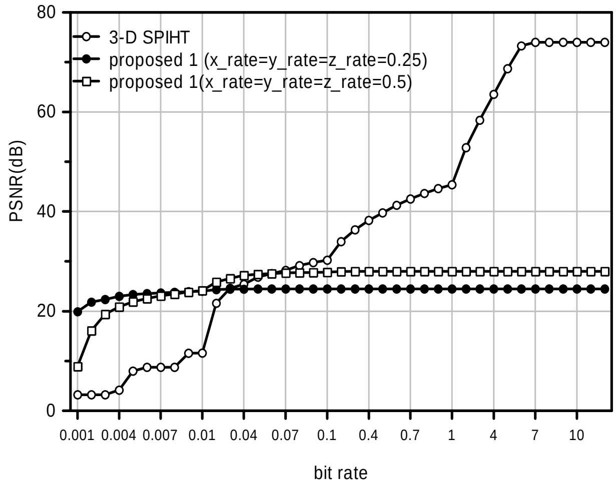

Fig. 4. Performance saturation of the compression algorithm with resizing.

3 Hybrid Compression with Resizing

In order to address the saturation problem, we propose a hybrid compression method for hyperspectral images. Fig. 5 illustrates the proposed hybrid compression method. First, original images are reduced and then compressed using a conventional 3-D image compression method such as the 3-D SPIHT algorithm. We allocate bits to compress the reduced images until the performance is saturated. When adding more bits does not improve the compression performance, we decode the encoded data of the reduced images. The reduced images are enlarged by the same factor, producing reconstructed images whose size is identical to that of the original images. Then, we compute the differences images which are obtained by subtracting the reconstructed images from the original images. When more bits are added, the difference images are encoded. In other words, when adding more bits for compression of the reduced images fails to improve the performance, we start to use additional bits to encode the difference images.

At the decoder side, we first decode the encoded data of the reduced images, producing reduced images. Then we enlarge the reduced images, producing reconstructed images whose size is the same as that of the original images. If there is encoded data for the difference images, the encoded data is decoded, producing difference images which are added to the reconstructed images. The decoding procedure is illustrated in Fig. 6.

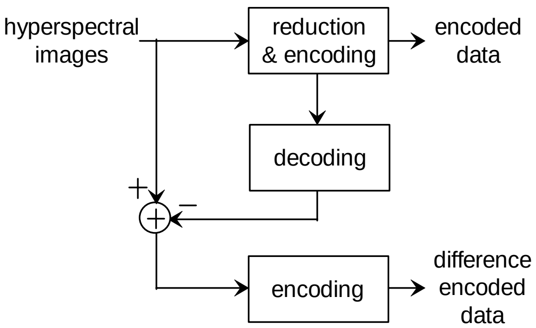

Fig. 5. Block-diagram of the encoder of the hybrid algorithm.

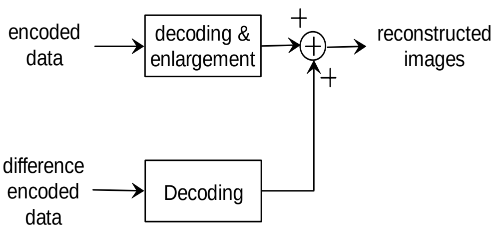

Fig. 6. Block-diagram of decoder of the hybrid algorithm.

4 Experiments and Results

Experiments are conducted using the AVIRIS (Airbone Visible Infrared Imaging Spectrometer). The data set contains 220 spectral bands and the size of image is 614 by 2166. From the image, we selected two sub-regions whose sizes are 256 by 256. The Fig. 7 and Fig. 11 show the selected areas.

In the AVIRIS data, each channel is assumed to have 12-bit resolution. In this paper, the bit-rate is defined on a per-band basis. In other words, 1 bpp indicates 1 bit per pixel for each band, which corresponds to compression rate of 12 : 1. In order to evaluate the performance of the proposed algorithm, we use the PSNR, which is define as

$$PSNR = 10\log_{10}\left[\frac{4095^2}{\frac{1}{N}\sum|s_o(x,y)-s_d(x,y)|^2}\right]$$

where N is the number of pixels of the original hyperspectral image, $s_o(x,y)$ is the pixel value of original image at (x,y) and $s_d(x,y)$ is the pixel value of reconstructed image. It is noted that PSNR is computed for each band and we compute the average PSNR of the entire bands.

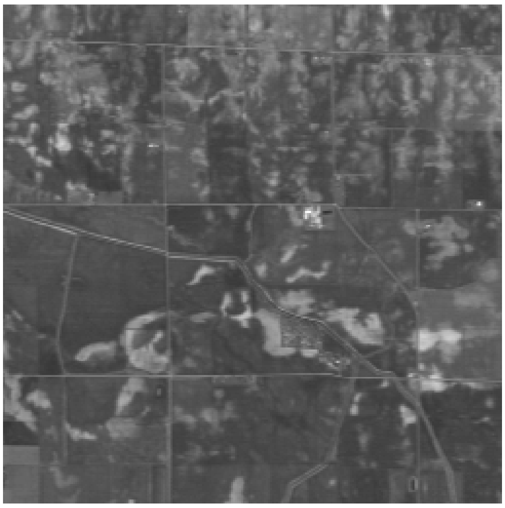

Fig. 7. An original image (test image 1).

Fig, 7 shows an original mage of test image 1. First, the images are reduced by a factor of 0.25. The decomposition level is 3. Along with the proposed hybrid compression, we also tested the conventional 3-D SPIHT algorithm without any resizing and the compression method with resizing only [1]. Fig. 8 shows performance comparison. As can be seen, the proposed hybrid compression method outperforms the conventional 3-D SPIHT algorithms at low bit rates and provides comparable performance even at high bit rates. On the other hand, the compression method with resizing only [1] outperforms the conventional 3-D SPIHT at low bit rates and then the performance become saturated. At high bit rates, the compression method with resizing only is significantly outperformed by the conventional 3-D SPIHT.

In Fig. 9, we increased the number of decomposition level to 4. It can be seen that overall performance are improved for all the compression methods. Fig. 10 shows an example of reconstructed images obtained by the proposed hybrid method. The bit per pixel is 0.06 and the PSNR is 29.19dB.

Fig. 11 shows another original mage (test image 2). As previously, the images are first reduced by a factor of 0.25. Similar performance was observed. Fig. 14 shows an example of reconstructed images. The bit per pixel is 0.1 and the PSNR is 31.30dB.

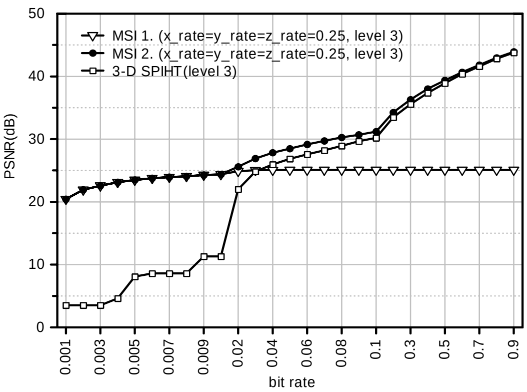

Fig. 8. Performance comparison of test image 1 (decomposition level=3).

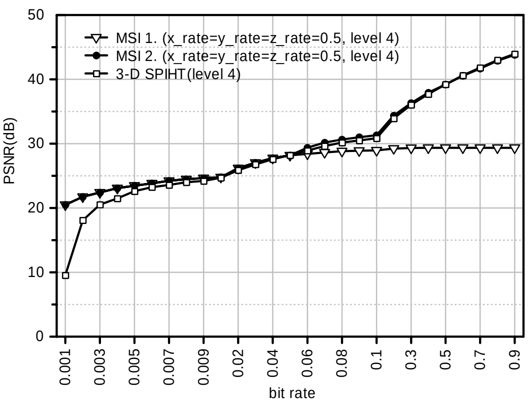

Fig. 9. Performance comparison of test image 1 (decomposition level=4).

Fig. 10. An example of reconstructed images obtained by the proposed hybrid method (test image 1, bpp=0.06, PSNR=29.19dB).

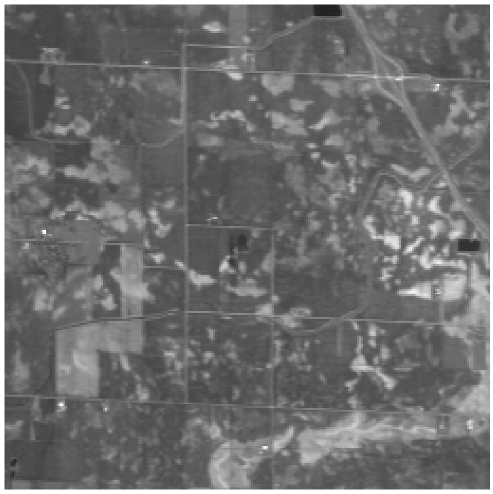

Fig. 11. An original image (test image 2).

5 Conclusions

We proposed a hybrid compression method which uses prior image reduction and difference coding. Although a 3-D image coding method with image reduction provides improved performance at low bit rates, the performance becomes saturated as the bit rate increases. We solved this saturation problem by introducing hybrid compression. In the hybrid compression method, we first reduce 3-D images and compress the reduced images using a conventional compression algorithm. When the performance is saturated, we compute the difference images which are obtained by subtracting reconstructed images from the original images and then encode the difference images. Experimental results show that the proposed hybrid algorithm provides better performance than the conventional 3-D SPIHT algorithm at low bit rates and is comparable to the conventional 3-D SPIHT algorithm at higher bit rates.

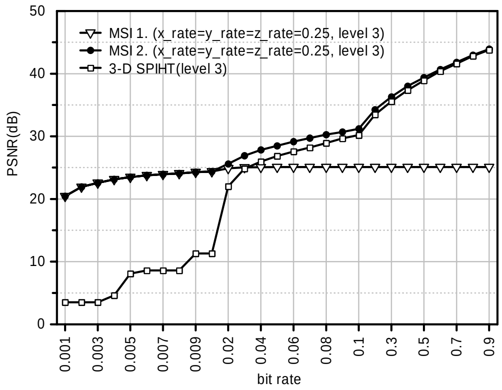

Fig. 12. Performance comparison of test image 2 (decomposition level=3).

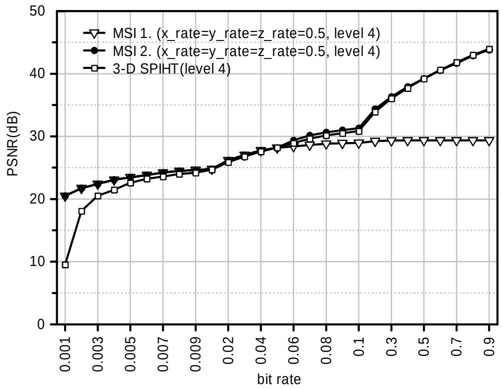

Fig. 13. Performance comparison of test image 2 (decomposition level=4).

Fig. 14. An example of reconstructed images obtained by the proposed hybrid method (test image 2, bpp=0.1, PSNR=31.30dB).

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