Efficient Adaptive Lossless Compression of Hyperspectral Data using Enhanced DPCM

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ABSTRACT
Hyperspectral sensors are imaging spectrometry sensors that generate useful information about climate and the earth surface in numerous contiguous narrow spectral bands, and are widely used in resource management, agriculture, environmental monitoring, etc. Compression of the Hyperspectral data helps in long-term storage and transmission systems. Lossless compression is preferred for high-detail data, such as Hyperspectral data. There are a few well-known methods for lossless compression, such as JPEG standards, and some other previously proposed methods. However, improving the compression ratio of previous methods is the major focus in Hyperspectral-data compression. This paper introduces two new lossless compression methods. One of these methods is adaptive and powerful for the compression of Hyperspectral data, which is based on separating the bands with different specifications and compressing each one efficiently. The new proposed methods improve the compression ratio of the JPEG standards, save storage space, and speed up the transmission system. The proposed methods are applied on different test cases, and the results are evaluated and compared with other state-of-the-art compression methods, such as lossless JPEG and JPEG2000.

Keywords
Hyperspectral data, Adaptive Compression, Lossless Compression, DPCM, Enhanced DPCM transformation (EDT).

1. INTRODUCTION
HYPERSPECTRAL imaging systems provide data with high spectral resolution that contains a range of wave- lengths from ultraviolet to infrared. However, Hyperspectral remote sensors collect image data simultaneously in dozens or even hundreds of narrow, adjacent spectral bands [1]. Each spectral band represents an image and all images make a three dimensional Hyperspectral cube. Fig. 1 shows an example of such a Hyperspectral cube. The values of all pixels in the one spectral band make a gray scale image with two dimensions, which are spatial and spatial. Each pixel corresponds to the reflected radiation of the specific region of the earth and has multiple values in spectral bands. Left image of Fig. 1 shows

a histogram of the one pixel with multiple values for each band in spectral dimension.

Hyperspectral images have been widely used in numerous applications, such as resource management, agriculture, environmental monitoring, mineral exploration, and climate observation. The sensors can generate more than one terabyte data in one day. Because of these enormous data acquisitions in a day, the use of a robust data compression technique has become very important for archiving and transferring purposes [2]. Because of the generation of highly accurate information about the atmosphere, clouds, and surface parameters provided by the Hyperspectral sensors, lossy compression techniques are not acceptable in this case [3]. The economics of transmission and mass-storage purposes of the large volume of data accumulated by these sensors demonstrate that efficient compression is very important in this technology [4]. There are a few well-known methods for lossless compression, such as JPEG standards. For example, JPEG2000 is widely used in lossless compression. These methods are generated for all kinds of images [5, 6]. As Hyperspectral data are created from different bands that could have different specifications, applying a single method for all the bands without considering their specifications may not be an efficient tool. In addition, there are some methods that are specifically designed for Hyperspectral data which have got advantage of predictive-coding-based such as M-CALIC [7] or the other proposed method [8], where band clustering techniques have been employed. The other method, which used a quantization technique with band adaptive quantization factors, was introduced in [9] to reduce the lookup table size.

In this paper, two new lossless compression methods are introduced: one of these methods is an adaptive lossless compression algorithm for Hyperspectral data, in which the corrupted bands are separated from the other bands and coded in a very short manner. Furthermore, the other bands are compressed using enhanced DPCM transformation (EDT) and optimized Huffman encoding. This method leads to higher compression ratios compared with one of the authors' methods and other previous methods. The other method is the non-adaptive scheme. In addition, it should be noted that this method has low computational complexity.
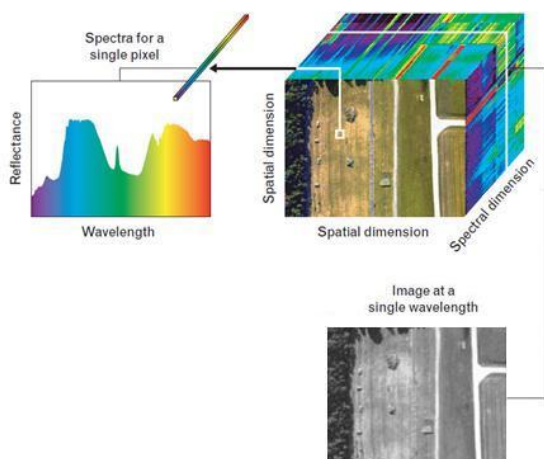
Figure 1. An Example of a Hyperspectral Cube

This paper is organized as follows. In Section 2, previous compression standards are briefly explained. In Section 3, the proposed lossless compression methods, their structures, specifications, and lossless models are presented. Section 4 is devoted to the experimental results and comparison of the new methods with the previous ones. Finally, Section 5 presents the concluding remarks and future works.

2. RELATED WORK

Image compression can be lossy or lossless. Lossless compression is used when information on the images is important and loss of information is not acceptable, such as medical images and remote-sensing (RS) images. It consists of two major parts: transformation and entropy encoding [10]. JPEG standards are the most important lossless image compressions and are described in the following section.

2.1 Lossless JPEG

JPEG is the very famous ISO/ITU-T JPEG is a very famous ISO/ITU-T standard that was created in the late 1980s [5]. Lossless JPEG is one of the several JPEG standards. In lossless mode, the image is transformed by differential pulse code modulation (DPCM), and then Huffman is applied for encoding. DPCM is based on predicting the image pixels from the neighboring pixel by a specific equation and calculating the error of prediction. The neighboring position and different predictor equations are shown in Fig. 2.
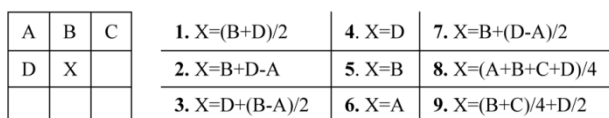

Figure 2. Neighboring Pixels in DPCM and Prediction Equations [10].

Better prediction causes the predicted pixel to be closer to the original pixel value, and, therefore, results in less prediction error value.

2.2 JPEG-LS

JPEG-LS standard of coding still images provides lossless and near-lossless compression. The baseline system or the lossless scheme is achieved by adaptive prediction, context modeling, and Golomb coding [5].

2.3 JPEG2000

JPEG2000 is based on the discrete wavelet transform (DWT), scalar quantization, context modeling, arithmetic coding, and

post-compression rate allocation [5]. JPEG2000 works well and gives a good compression ratio especially for high-detail images, because it analyzes the details and the approximation in the transformation step and decorrelates them. However, JPEG2000 has high computational complexity.

3. PROPOSED METHOD

3.1 Title and Authors

In this section, novel lossless image compression is proposed. This new method consists of EDT11 and optimized Huffman encoding.

3.1.1 EDT

This is an efficient transformation because of its high ability of redundancy reduction and energy compaction. In addition, it is more powerful in prediction, compared with the previous predictive schemes, such as DPCM. As can be seen in Fig. 3, for transforming an image by EDT, first, two divides the input image intensities. Then, the remainders and quotients are saved in different memories. The divided intensities are predicted by one of the prediction equations shown in Fig. 2. It is almost certain that the probability of correct prediction in the smaller interval is more than the bigger interval. After predicting the divided image intensities, the predicted image is multiplied by two and added to the remainders to create the predicted image. Furthermore, the prediction error can be easily calculated by subtracting the main image from the predicted image [11].

As entropy analysis is one of the best ways to evaluate any transformation, such as EDT, in the following paragraph, the entropy and the way it calculates are described.

The entropy value is a measure for the possibility of compression by encoding. Entropy indicates the required bit per pixel amount. In fact, the entropy shows how much compression is possible for that image and presents this information in bit per pixel. For example, when one says that the entropy of an 8-bit image is 6.3, it means that the required bit per pixel amount is 6.3 bit per pixel for that image; therefore, such a range of compressions is possible for that image. Also, according to Shannon's first theorem [12], it is possible to reach an entropy value using an encoder. The entropy value (E) of any given image is calculated as follows:

$$E = -\sum_{k=0}^{L-1} p_r(r) \log_2 p_r(r) \tag{1}$$

Where r is the intensity value L is the number of intensity values used to present the image, and p_r is the probability of intensities. For an image with a depth of 8 bits, L would be equal to 256 and r would be in the range of 0-255. The histogram of the given image can be used to calculate the intensities' probabilities [12]. An image with a less entropy value indicates that more compression is possible. Transformation increases energy compaction, and, as a result, the probability of each intensity or source symbols increases, which leads to less redundancy and less entropy.
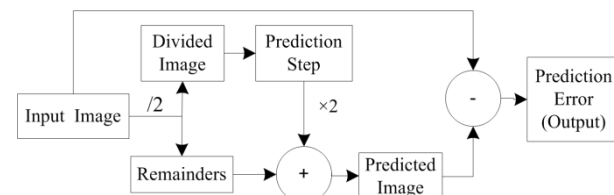

Figure 3. Block diagram of EDT

3.1.2 Optimized Huffman Encoding

Huffman codes the image intensities based on their probability and convert them as a bit-stream. Therefore, the Huffman dictionary, which includes intensity codes, needs to be saved as an overhead. After calculating the prediction error, all the values remain in the range of $-2k + 1$ and $2k - 1$. For example, for a gray scale image with an 8-bit depth, this interval remains between -255 and 255. Therefore, Huffman encoding may need a dictionary that could cover this interval. However, the transformed image by EDT has only even values. To have an optimized entropy encoder, the proposed method uses only even values of the aforementioned interval for the Huffman dictionary. As a result, a smaller dictionary is achieved and fewer headers are needed.

3.2 Extended New Lossless Compression Method (ENLCM)

Figure 4 illustrates the general engine of the second proposed method. First, the input Hyperspectral data's histogram is analyzed. Subsequently, the corrupted bands are separated from the other bands. These bands do not carry information and include only one color or value for all the pixel values. However, these corrupted bands should also be saved, because they are required in the reconstruction phase for placing the bands in the correct orders. When the corrupted bands are separated, they are coded in the smallest form possible. Ten bytes are considered for this purpose, which will be described subsequently. The other bands that include the most important information will be compressed with the NLCM, and are described in Section 3.1. Finally, the outputs of these two compression methods are added together to create the final compressed bit-stream, which is ready for storage or transmission. The compressed bit-stream is the coded version of the input Hyperspectral data, which needs less space for storage. In this proposed method, an adaptive scheme is introduced to separate the corrupted and the uncorrupted bands. In the following paragraph, compression of the corrupted and the uncorrupted bands is described in detail.
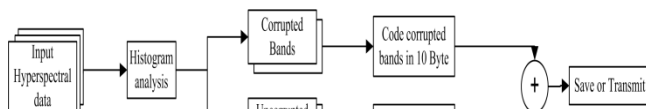

Figure 4. General Engine of ENLCM

3.2.1 Compression of Corrupted Bands

The first step of the proposed method is a histogram evaluation, where each image's histogram value is analyzed to determine whether it is corrupted or not. In this method, any image that has only one value for its histogram is a corrupted band. Figure 5 indicates an example of a corrupted image histogram and an uncorrupted band image histogram. As can be seen, the uncorrupted image has different intensity values, but the other one has only one value, which is mostly 0 or 255. However, in this paper, only the bands with one value are compressed by this coding scheme.
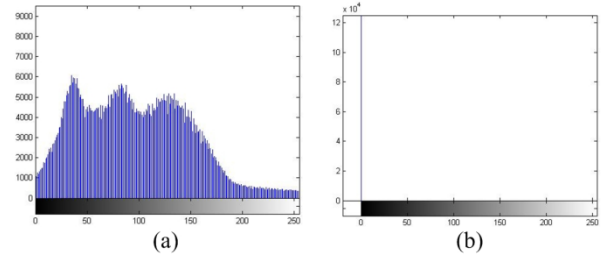

Figure 5. a) An Uncorrupted Band Histogram, b) A Corrupted Band Histogram

When the histogram is evaluated and the corrupted band is specified, the coding step begins. In the coding step, 10 bytes are assigned for the corrupted bands, where specific codes are assigned for the starting and finishing 2 bytes. These code words separate them from the other bands and help in the reconstruction phase. The third byte indicates the number of corrupted band, the fourth byte is used to show the intensity value of the band, and the other bytes are aligned for the unpredictable headers. Figure 6 illustrates these bytes.

Figure 6. The contents of the 10 assigned Bytes for Corrupted Bands

3.2.2 Compression of Uncorrupted Bands

As shown in Fig. 3, the uncorrupted bands compressed by the proposed NLCM comprise the EDT and the optimized Huffman.

The energy compaction of EDT is more than that of DPCM because the outputs of EDT have less variety in its values. All the possible values for the EDT outputs are factors of two and include only even values. Therefore, the varieties are twice smaller than those of the DPCM. The energy-compaction improvement of the EDT can be calculated from their entropy values. The entropy value decreases with the enhancing energy compaction and causes more compression. Assume an image with equal probability distribution for all intensities. According to (1) and for such an image, the entropy value can be calculated as:

$$E = -M \times N \left(\frac{\log_2(\frac{1}{L})}{M \times N} \right)$$

$$= -\log_2\frac{1}{L} = k \quad where \quad L = 2^k \tag{2}$$

Where L is the number of intensities and K is the image depth. For an 8-bit image, L is equal to 256. Therefore, the entropy is equal to k or 8 for the described image. When the image intensities are divided before prediction, then:

$$L_{EDT} = 2^{k-1} = \frac{L}{2} \tag{3}$$

Where LEDT is the number of intensities for the divided image. From (2) and (3), for an image transformed by EDT:

$$E_{EDT} = -\log_2\left(\frac{1}{L_{EDT}}\right) = -\log_2\left(\frac{2}{L}\right) = k - 1 \tag{4}$$

This means that the required bit per pixel or entropy value would be 7, and, as a result, about 0.125 improvements in the compression ratio would be achieved. In addition, it should also be noted that the inverse EDT (IEDT) could be easily achieved by applying the following equation on the transformed image:

$$I(i,j) - I(i,j) \ mod \ n = T(i,j) + \lfloor \frac{prediction \ by \ equation \ \#k}{n} \rfloor \times n \qquad (5)$$

After applying EDT on the uncorrupted bands, the optimized Huffman, as described in Section 3.1.2, en- codes the bands and converts them to compressed bit-stream. At this stage of work, all the corrupted and the uncorrupted bands are compressed and added together to form the final bit-stream.

As shown in the previous equations, the EDT causes the entropy of the image and is responsible for some percentage of improvement in reducing the entropy amount of the transformed image compared with the DPCM. Subsequently, using an effective Huffman encoder, the bit rate or the required bit per pixel amount for each image would be very close to the entropy value. Therefore, the new method is efficient. However, for the corrupted bands, another algorithm is used to improve the total compression ratio of the Hyperspectral data. Even then, in some cases, more than 25 percent of the Hyperspectral bands found to be corrupted.

4. EXPERIMENTAL RESULTS

In this section, the proposed methods are applied on two different Hyperspectral data. One of the differences of these two test cases is the number of the corrupted bands. The first one has numerous corrupted bands, but the other has only a few corrupted bands. Therefore, there is the possibility to test the proposed method in both the cases. It should be noted that the lossless JPEG and the proposed compression methods are accomplished by the MATLAB and the JPEG2000 compression by ENVI software version 4.4.

The first test case is a Hyperspectral image that consists of 242 bands. Each band consists of 256×3128 pixels with an 8-bit depth and is captured by Hyperion. Hyperion is one of the Hyperspectral sensors that have been fixed on the Earth Observer (EO-1) satellite in a 705-km sun-synchronous orbit at a 98.7-degree inclination. Hyperion is a push broom spectrometer and provides resolution of the surface properties in hundreds of spectral bands in the range of 0.4-2.35 μm at 30×30 m spatial resolution.

The Hyperspectral Digital Imagery Collection Experiment (HYDICE) sensor captured the second test case. HYDICE is a push broom imaging spectrometer, which collected data in 210 bands in the range of 0.4-2.5 μm at an IFOV of 1-4 m, depending on the altitude of the aircraft and ground speed. In this case, the sensor collected data over the Washington DC Mall in 191 channel sets. This data set contained 1280 scan lines with 307 pixels in each scan line; thus, each band would be a 1280×307 image with an 8-bit depth. Figure 7 illustrates one of the bands of this test case.

Figure 7. A Band of the Second Test Case

Figure 8 illustrates the entropy value of all the bands of these two Hyperspectral data test cases. As can be seen, the entropy value of some bands in the first test case is equal to zero. This signifies that they have only one value for all the pixels, and one can consider them as the corrupted bands. It can be observed that in the first test case, there are 62 corrupted bands, indicating that more than 25 percent of the bands are

corrupted. Furthermore, in the second test case, it can noted that there are just a few bands with an entropy equal to zero, as well as some bands with low entropy values. These are highly correlated in the neighboring pixels and include less amount of information compared with the other bands. The compression ratio of these bands is expected to be more than the others. In addition, the proposed methods include the predictive scheme, and due to the neighboring correlation of the large amounts of bands, it can be efficient for this test case as well.
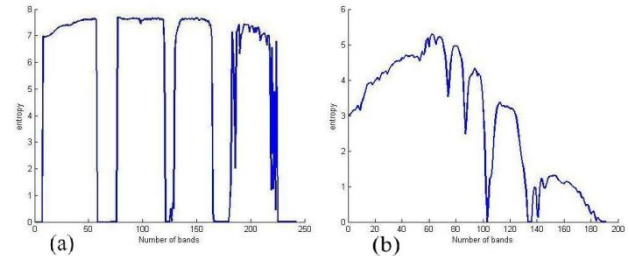

Figure 8. The Entropy Values of All the Bands of a) First Test Case, b) Second Test Case

It is almost certain that after transformation, the entropy value of the transformed image is reduced. Lossless JPEG, lossless version of JPEG2000, and the new proposed methods are applied on these Hyperspectral data test cases, and the compression ratios are presented in Table 1. Furthermore, the NLCM has been applied on the test cases and its ratios are presented in the table to have a better understanding about the difference between the adaptive method (ENLCM) and the simple one (NLCM). The compression ratio of the Hyperspectral data is calculated as:

$$CR = \frac{Sum \ of \ All \ the \ Bands \ Sizes}{Sum \ of \ Compressed \ Bit\text{-}Streams \ Sizes} \qquad (6)$$

In ENLCM, the sum of the compressed bit-streams consists of the coded version of the corrupted bands and the compressed bit-streams obtained from the other path.

In the first test case, the ENLCM gives the best result and has the highest compression ratio, while the NLCM works better than the lossless JPEG. However, JPEG2000 has a better compression ratio than the NLCM because of better compression of the corrupted bands. The only advantage of NLCM is its simplicity, which is suitable for real-time systems that need a simple and fast algorithm. ENLCM works efficiently and compresses each band as required. Compared with the previous method, ENLCM demonstrates an increased compression ratio of more than 15 percent, while JPEG2000 shows an increase of more than 5 percent. Furthermore, the compression ratio for each band is examined to observe the performance of different methods. As shown in Fig. 9, the ENLCM and the NLCM work close to each other in most cases. However, in the corrupted bands, the compression ratio of ENLCM is much higher than the others. Therefore, on the whole, it can be concluded that ENLCM works better than the others.

Table 1. Lossless compression ratio of both test cases obtained by different compression algorithms

Test Case	Lossless-JPEG	JP2	NLCM	ENLCM
First	2.327	2.778	2.58	2.92
Second	2.375	2.04	3.76	3.78

Furthermore, it should be noted that to have a better view of the values, the compression ratio with a value of more than 5 is not included in the plot, because the values of the compression ratio of the corrupted bands are high. For instance, band number 75, which is a corrupted band, has a compression ratio of 8.25 and 1190.19 for lossless JPEG and JPEG2000, respectively. However, the proposed methods' compression ratio is equal to 82599. The compression ratio estimations are based on (6). In addition, it is clear from Fig. 9 that the proposed methods are better than the JPEG2000 for most of the bands.

ENLCM demonstrates the best result in the second test case. One point can be concluded from this experiment. One of the differences here is that JPEG2000 shows the worst result among the three methods. It shows that a predictive scheme is better for this test case. Also, due to the improvement of the new methods from lossless JPEG, the improvement in the compression ratio is predictable. In other words, the predictive scheme could be a good choice for Hyperspectral data compression. The compression ratio plot is shown in Fig. 10. As expected, the compression ratios are high in the low-detail bands that had less entropy values. Furthermore, the efficiency of the proposed methods is visually tangible. In the second test case, about 50 percent improvement in the compression ratio could be observed, and, in this case, the compression system is computationally simple.
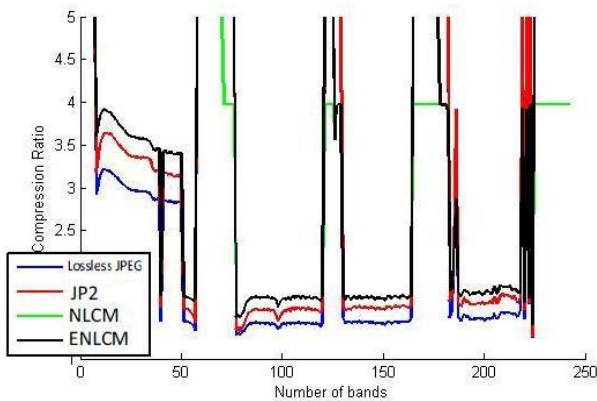

Figure 9. The Compression Ratio of Different Methods for All the Bands of the First Test Case
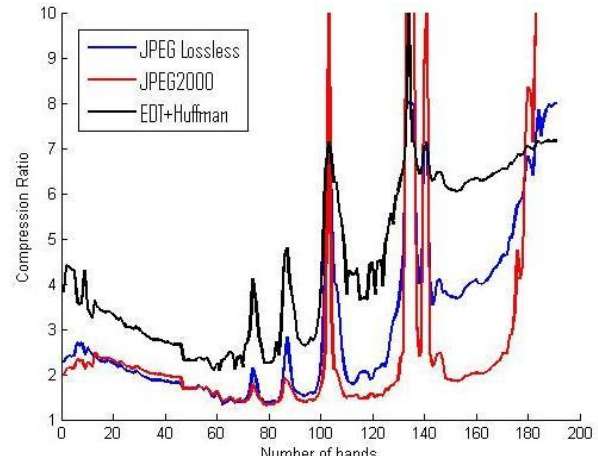

Figure 10. The Compression Ratio of Different Methods for All the Bands of the Second Test Case

4.1 Functionality

Finally Table 2 indicates a total comparison of the proposed method with the previous ones in different sights for Hyperspectral images. The compression ratio for lossless and lossy versions is included too. Some information of different JPEG standards included in Table 2 is brought from [6]. As can be seen, in most cases the NLCM is powerful and efficient. However, JPEG2000 is more powerful in some cases such as functionality. However, it is not necessary for our purpose. Finally, we can conclude that the introduced compression method is more efficient than other methods for the lossless compression of Hyperspectral images when the simplicity of hardware implementation is important.

Table 2. Functionality Evaluation for Different Methods

Functionality	Lossless JPEG	JPEG-LS	JP2	NLCM
Transformation Ability	•••	•••	••	••••
Low Complexity	•••••	•••••	••	•••••
Functionality	•	•	•••••	••
Lossless Compression	•	••••	•••	•••••
Lossy Compression	•••	•	•••••	•••

5. CONCLUSION

In this study, due to the specification of the Hyperspectral data, two novel methods (NLCM and ENLCM) for lossless compression of Hyperspectral data have been introduced. Compared with NLCM, the ENLCM is based on separating the corrupted bands from the others, acts on each band depending on its specification, and compresses the corrupted and the uncorrupted bands with different schemes. Thus, the ENLCM is much more efficient compared with the NLCM. In fact, ENLCM showed improved compression ratio than the previous methods. This improvement is dependent on the number of corrupted bands. The ENLCM was tested on two different cases and compared with JPEG standards. In the first test case, more than 12 percent improvement in the compression ratio occurred compared with the previous methods, and about 50 percent improvement was observed in the second test case. This huge difference in the improvement in the compression ratio is because of the specifications of the second test case, which has numerous neighboring

correlations. Improving EDT, testing other encoders, and hardware implementation of the proposed method are some of the areas of research, which must be carried out in future.

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