Shadna Yadav, Vimal Gupta / International Journal of Engineering Research and Applications (IJERA)
ISSN: 2248-9622 www.ijera.com
Vol. 2, Issue 2, Mar-Apr 2012, pp.1038-1042

A 4-D Sequential Multispectral Lossless Images Compression Over Changed Data Using LZW Techniques

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Abstract
For the large-scale acquisition of hyper-spectral or multispectral images, data distribution challenges the capabilities of available transmission technologies. Multispectral image is one that captures image data at specific frequencies across the electromagnetic spectrum. It is therefore common to include data compression as part of a distribution system for remotely sensed imagery. While individual images can be compressed for transmission by taking into account the inherent spatial and spectral redundancy, a distribution system for remotely sensed images can also take account of the sub-bands of images. The sub-bands of the images provide an additional opportunity for data compression. Sub-band is used to decrease the bandwidth of transmission by separating the frequency band. In this work we show that a four-dimensional approach (exploiting spatial, spectral and changed data within sub-band of image) to the compression of sub-bands of the images provides significant improvement over an approach that increases higher compression ratio. The Landsat ETM data (images) recorded over Canberra, Australia, in 2000 and 2001. Temporal reduction is achievable and the degree of compression is higher when imaged areas have no significant changes. The 4-D compression approach is based on the changed data among different sub-bands of image. 4-D compression approach is applicable for remotely sensed data to change the sub-bands of images, and separate the data.

Keywords: *Multispectral images, LZW algorithms, compression, entropy, correlation*

1. Introduction
Images are an important part of today's digital world. However, due to the large quantity of data needed to represent modern imagery the storage of such data can be expensive. Thus, work on efficient image storage (image compression) has the potential to reduce storage costs and enable new applications. Many image compression schemes are lossy, that is they sacrifice image information to achieve very compact storage. Although this is acceptable for many applications, some environments require that compression not alter the image data.

Multispectral image is one that captures images data at specific frequencies across the electromagnetic spectrum .various remote sensing sensors such as multispectral hyper spectral and synthetic aperture radar generate a large volume of digital images. Two dimensional spatial coding has been adapted to remove the spatial correlation in the image data. In addition, context modeling has been used for the adaptive correction to remove any correlation that remains in the residuals, Third (spectral) dimension's correlation has also been found strong especially for hyper spectral data and has been used for effective inter-band prediction. The 4-D compression approach is based on the temporal redundancy to compress the sequential multispectral images. The 4-D compression approach is applicable for remotely sensed data to change the sequence of images, and separate the data. Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies.

2. Proposed Objective
The main objective of the 4-D compression approach is to compress the changed data detected in the image by exploiting its redundancy between the sub-bands of images.

3. Proposed Lossless Compression Technique
3.1 LZW compression
LZW (Lempel- Ziv-Welch) is a dictionary based coding. LZW (Lempel- Ziv-Welch) is a dictionary based coding. Dictionary based coding can be static or dynamic. In static dictionary coding, dictionary is fixed during the encoding and decoding processes. In dynamic dictionary coding, the dictionary is updated on fly. LZW is widely used in computer industry and is implemented as compress command on UNIX. LZW is named after Abraham Lempel, Jakob Ziv and Terry Welch, the scientists who developed this compression. It is a lossless 'dictionary based' compression algorithm. Dictionary based algorithms scan a file for sequences of data that occur more than once. These sequences are then stored in a dictionary and within the compressed file, references are put where-ever repetitive data occurred. LZW compression replaces strings of characters with single codes. The code that the LZW algorithm outputs can be of any arbitrary length, but it must have more bits in it than a single character.

An inverse process called decompression is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the

visual quality of the reconstructed image as close to the original image as possible.
The decompression works by reading a value from the encoded input and outputting the corresponding string from the initialized dictionary. At the same time it obtains the next value from the input, and adds to the dictionary the concatenation of the string just output and the first character of the string obtained by decoding the next input value. The decoder then proceeds to the next input value (which was already read in as the "next value" in the previous pass) and repeats the process until there is no more input, at which point the final input value is decoded without any more additions to the dictionary.

3.2Algorithm

A high level view of the compression algorithm is shown here:

1. Initialize the dictionary to contain all strings of length one.
2. Find the longest string W in the dictionary that matches the current input.
3. Emit the dictionary index for W to output and remove W from the input.
4. Add W followed by the next symbol in the input to the dictionary.
5. Go to Step 2.

A computer will render these as strings of bits. Five-bit codes are needed to give sufficient combinations to encompass this set of 27 values. The dictionary is initialized with these 27 values. As the dictionary grows, the codes will need to grow in width to accommodate the additional entries. A 5-bit code gives $2^5 = 32$ possible combinations of bits, so when the 33rd dictionary word is created, the algorithm will have to switch at that point from 5-bit strings to 6-bit strings (for *all* code values, including those which were previously output with only five bits). Note that since the all-zero code 00000 is used, and is labeled "0", the 33rd dictionary entry will be labeled 32. (Previously generated output is not affected by the code-width change, but once a 6-bit value is generated in the dictionary, it could conceivably be the next code emitted, so the width for subsequent output shifts to 6 bits to accommodate that.)

4. Sub-band decomposition

To separate the image into a different frequency band is called sub-band.

- Sub-band is used to decrease the bandwidth of transmission by separating the frequency band.
- The sub-band decomposition has the advantages, complexity is reduced by dividing the image into sub-bands.

5. Proposed Architecture

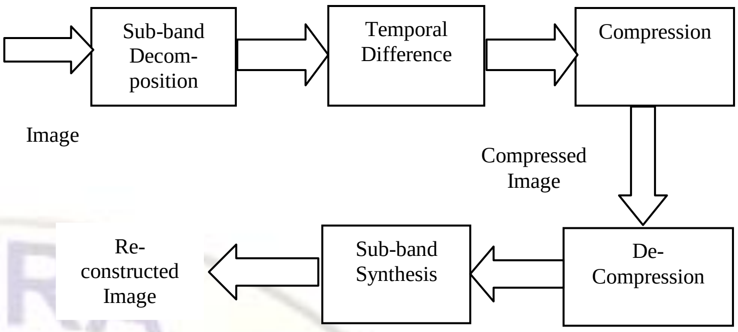

Fig.1 Block diagram of image compression

The block diagram for the compression of a compressed multispectral image is shown in Fig.1. The proposed architecture discusses the following steps-

5.1Sub-band decomposition

Sub band coding is used to decrease the bandwidth of transmission by separating the frequency band and using different level quantizers in each band. The quantization level can be chosen to have more resolution in bands that are more sensitive to noise and to have less resolution in bands where quantization noise doesn't degrade the signal quality.

5.2Temporal difference

Temporal difference is used to find the difference between the sub band of image, there are some similar difference and some unsimilar difference. We extract the similarities, and transmit the unsimilar difference.

5.3Compression

Image compression reduces the number of bits required to represent an image by taking advantage of these redundancies.

LZW (Lempel- Ziv –Welch) is a dictionary based coding. Dictionary based coding can be static or dynamic. In static dictionary coding, dictionary is fixed during the encoding and decoding processes.

5.4 Decompression

Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. An inverse process called decompression (decoding) is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible.

5.5 Sub-band synthesis

Sub-band synthesis is the inverse of the sub-band decomposition. Sub band coding is used to decrease the bandwidth of transmission by separating the frequency band and using different level quantizes in each band. The quantization level can be chosen to have more resolution in bands that are more sensitive to noise and to have less resolution in bands where quantization noise doesn't degrade the signal quality.

6 Experimental Results

6.1 Introduction

In the following section, the proposed algorithm is tested with multispectral images of Landsat ETM data recorded over Canberra, Australia, in 2000 and 2001. The scheme takes as input a multispectral image. It first generates the 7 bands of the multispectral image. After decomposition of bands it generates multispectral raw image from summarization of 7 bands. Then using LZW algorithm that compares the original and compressed entropy for better compression ratio. We used all seven bands of the image. A correlation matrix was generated for the seven bands. 4D compression is the best at each band. The performance of 4-D compression is stable across all the bands, and provides best results overall.

6.2 Compression ratio

The performance of a lossless image compression algorithm is assessed by the compression ratio**.** Compression ratio is defined as:

Table1 results of the images

Image	Original size (bytes)	Compressed size (bytes)	Compression Ratio
paris.lan	1835428	1607982	0.876
littlecoriver.lan	1835428	1817824	0.990
mississippi.lan	1835428	941436	0.513
montana.lan	1835428	1292650	0.704
rio.lan	1835428	1479596	0.806
tokyo.lan	1835428	1076908	0.587

Compression ratio = compressed image / original image

We take an image paris.lan, and calculate the original size of the image and compressed size of the image, minimum compressed size means better compression ratio.

6.3Entropy in Bits/ Pixel

Table 2 Entropy comparison for the Bands of the image paris.lan

Band	Uncompressed (Original entropy)	Compressed entropy
b1	5.8616	5.8616
b2	4.9738	0
b3	5.7338	0.1066
b4	6.1861	0.1406
b5	6.4180	0.0773
b6	4.8526	0.0037
b7	5.7992	0.0021

From the above Table the entropy achieved by the proposed technique is always smaller than that of the original image for the bands of image.

6.4 Mutual correlation table

Correlation between bands returns a ***p***-by-***p*** matrix containing the pairwise correlation between each pair of rows to columns.

Syntax

r = corr2(A,B)

r = corr2(A,B) computes the correlation coefficient between A and B, where A and B are matrices of the same size.

The correlation between band (1,1), band (2,2), band (3,3), band (4,4), band (5,5), band (6,6), band (7,7) is one.

Table 3 Existing mutual correlation between bands of multispectral image paris.lan

	Band1	Band2	Band3	Band4	Band5	Band7
Band1	1	**0.9464**	0.8843	0.1532	0.2979	0.6104
Band2	0.9464	1	**0.9427**	0.2603	0.3830	0.6792
Band3	0.8843	0.9427	1	0.2123	0.4797	**0.7684**
Band4	0.1532	0.2603	0.2123	1	**0.4352**	0.3293
Band5	0.2979	0.3830	0.4797	0.4352	1	**0.8745**
Band7	0.6104	0.6792	0.7684	0.3293	0.8745	1

The 4- D compression framework was tested and compared with other bands of the image of Landsat ETM data recorded over Canberra, Australia, in 2000 and 2001.

We used all six bands except band 6 of the image (band 6 was omitted because it has a lower resolution to the other bands). This region contains a small changed area on the up right portion of the image. Overall it is dominated by the non changed areas.

In the spectral domain, a correlation matrix was generated for the six bands as given in (table 3). From these results, a correlation chain was formed: Band 1, Band 2, Band 3, Band 7, Band 5 and Band 4. The band at the top rank of this data set, Band 1, is selected for temporal prediction followed by spatial coding. Other bands are compressed through interband prediction according the order given in the correlation chain and individual spatial coding.

Table 4 Proposed mutual correlation between bands of multispectral image paris.lan

	Band1	Band2	Band3	Band4	Band5	Band6	Band7
Band1	1	**0.9513**	0.9166	-0.0331	0.4478	0.3523	0.6402
Band2	0.9513	1	**0.9666**	0.1517	0.6062	0.3119	0.7366
Band3	0.9166	0.9666	1	0.1038	0.6544	0.3791	**0.8145**
Band4	-.0331	0.1517	0.1038	1	**0.6507**	-.1730	0.2891
Band5	0.4478	0.6062	0.6544	0.6507	1	0.2040	**0.8820**
Band6	0.3523	0.3119	**0.3791**	-0.1730	0.2040	1	0.3696
Band7	0.6402	0.7366	0.8145	0.2891	0.8820	0.3696	1

The 4- D compression framework was tested and compared with other bands of the image paris.lan of Landsat ETM data recorded over Canberra, Australia, in 2000 and 2001. We used all seven bands of the image. In the spectral domain, a correlation matrix was generated for the seven bands as given in (table 4). From these results, a correlation chain was formed: Band 1, Band 2, Band 3, Band 7, Band 4, Band 5 and Band 6. The band at the top rank of this data set, Band 1, is selected for temporal prediction followed by spatial coding. Other bands are compressed through interband prediction according the order given in the correlation chain and individual spatial coding.

7. Related Previous Work

The given 4-d approach [6] is capable of compressing multispectral data set at higher compression rate. Spectral domain compression can be effective when the correlation between the bands is high. Spatial coding is generally effective, although it is more scenes dependent. A correlation chain is generated which ranks the bands from highest correlated to lowest to maximize the efficiency of between band predictions. Temporal reduction is achievable and the degree of compression is higher when imaged areas have *no significant changes.* When the image areas have a lot of significant changes, the existing approach have a less compression ratio. In order to achieve high compression ratio a separate compression technique is applied over that change data between sequences of images.

8. Conclusion

The proposed scheme used LZW algorithm for better compression ratio. It removes the lots of repetitive data, so transmission time is better. This is an approach to implement the lossless multi-spectral image compression with the temporal prediction in 'matlab'. We are using an algorithm for compression that is for temporal content removal.

A major advantage of this approach is it performs better, Compress for most of the multispectral images in terms of compression ratio. The algorithm gives good result, and higher compression ratio gained. This algorithm is simple in implementation. The proposed objective of the 4-D compression approach is to compress the changed data detected in the image by exploiting its redundancy between the sub-bands of images.

9. Future Work

In this thesis we have introduced a LZW lossless compression algorithm. The proposed approach is to compress the changed data detected in the image by exploiting its redundancy between the sub-bands of images.
For the sub-bands of images which contain higher compression ratio, the unified 4-D compression approach is effective. Further work will be on FPGA-Based on-board multi/hyper-spectral image compression system which contains hardware implementation.

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