Reducing the Compression Time of the Spectral DPCM for Lossless Compression of 3D Hyperspectral Sounding Data

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Abstract: - Image compression of hyperspectral sounder data is necessary because of the large storage requirements. The main objective of this paper is to present an efficient method for prediction coefficient estimation. The estimation is performed on a subset of the all image data points. The compression ratio remains almost the same with our method, at the same time the compression time is reduced to the half of the original compression time.

Key-Words: - Sounder images, Lossless compression, Image compression

1 Introduction

The main objective of this paper is to present an efficient predictor for lossless compression of hyperspectral sounder data. Image compression is a very important problem in the image-processing field since very large images require a large amount of storage space. One example of very large images is those taken with hyperspectral sensors. Hyperspectral images can be defined as images with a high spectral resolution, typically 100 to 300 different wavelengths [7]. The hyperspectral sounder images used in this research are taken with a Hyperspectral Environmental Sensor (HES).

The hyperspectral image has two spatial dimensions and one spectral dimension. The residual data produced by the compression algorithm is the coded difference between the original data and the predicted value. The original data can be recovered from the coded residual values. Different types of lossless compression algorithms based on prediction are well documented in the literature [1]-[4].

2 Theoretical background.

2.1 Hyperspectral Image Data

Different instruments are used for the acquisition of the data data at different wavelengths. An example of this type of instrument is a hyperspectral sensor. These sensors acquire data in a vast number of narrow and contiguous spectral bands, thus the use of the term hyperspectral. The hyperspectral sensors employed in this work are HES.

In the 3D sounding data, captured by AIRS, each image has 2108 spectral bands, 135 scan lines containing 90 cross-track footprints per scan line temporal and spectral resolutions is over thousand infrared channels and with spectral widths of the order of 0.5 wave number [2].

2.2 Spectral and Spatial Information

The goal of the lossless compression of the hyperspectral image is efficiency. Naturally all the information from the original image has to be maintained. Linear predictors are used for lossless compression because of their efficiency.

There exists two kinds of information in the hyperspectral images to make the prediction, spatial and spectral information.

The lossless compression algorithms can be seen as consisting of two stages: a prediction stage in which pixel values are predicted and a coding stage in which difference between the original and predicted values is computed and encoded. One of the most efficient linear prediction methods for HES images is introduced in [3].

The main purpose of a linear prediction algorithm is to establish interpixel dependencies using linear mathematical functions [7]. Then, based on this dependency we use only few pixel to find values of all other pixels. Pixels from the current and any previous bands can be involved. It will be explained in depth in Section 3.

Future random variables are predicted from past and present observable values in a prediction stage. Therefore, a prediction can be seen as a statistical estimation procedure. Linear prediction predicts the value for the next sample and computes the difference between predicted value and the original value [3]. Prediction of any current sample from some previous samples can be defined using linear or non-linear mathematical function. [7]

2.3 Spectral linear prediction with DPCM

This scheme, introduced in [3], uses a technique which implies prediction of each image band by involving number of bands along the image spectra. Each pixel is predicted using information provided by pixels in the previous bands in the same spatial position. An estimate for each pixel value is computed in the following way:

$$P'_{x,y,z} = \left\lfloor \sum_{i=1}^{M} a_{z,i} P_{x,y,z-i} + 1/2 \right\rfloor \quad (2.5)$$

where, $P_{x,y,z}$ is the value of the pixel at band z in spatial location (x,y), $a_{z,i}$, denote prediction coefficients (i =1….M), and M is the number of the image bands involved in prediction.

For each band the linear prediction is computed in such a way that the prediction coefficients minimize the expected value of the squared residual:

$$\sum_{x,y} (p'_{x,y,z} - p_{x,y,z})^2 \quad (2.6)$$

for band z

The entropy coding of the residual is performed band by band. Prediction coefficients are saved in a file that in entropy coded using an 8-bit entropy coder. The entropy coding part is performed with a range coder. The range coder used in our schemes is the Lundqvist's range coder [6].

3 Improvement DPCM in terms of time complexity

The idea is to reduce the time complexity of DCPM. Basically what we are doing in this improvement of DPCM is to reduce the number of the steps given for the loops when we are filling the matrices that are required to calculate the regression coefficients. It means that the two matrices, one vector of observations that contain all the pixels in the band, and one matrix of the levels of the independent variables, which perform the calculation of the regressions coefficients, are going to be smaller, more exactly smaller in number of rows. Normally for DPCM the number of rows in these matrices were the total number of pixels in the band, it was *number_of_rows = N*M,* where *N* and *M* are the spatial dimensions of the image. Now it can be reduced to: $number\_of\_rows = \left(\frac{N}{m}\right) \times \left(\frac{M}{m}\right)$, where m >0 $\in \mathrm{N}$. So that every mth pixel of every row/column is selected. As you will see in the Section 4, we have to select a right value of m in order not to reduce compression ratio, because with the reduction of size of both matrix, the coefficients got are not so accurate as with the normal matrix. So the ideal would be to select a right value of m in order to appreciate an improvement in the time complexity and not appreciate a decrease in the compress ratio.

4 Experimental Results

Algorithm described in Section 3 has been tested on HES airs_gran images. The images are available at [5]. For more information about these imges see Section 2.1.

The tests have been performed in computers with the following resources:

- AMD Athlon Thunderbird 1200 MHz,
- 1024 MB ECC SDRAM,
- Operating system: Debian GNU/Linux 3.0

Attributes of the tables:

Input Attributes:

- m : the values indicates the factor by which the sampling for the coefficient estimation is reduced

Output Attributes (Results):

- CR: Compression Ratio
- Time: time of execution [s]

When the value of the attribute m = 1, the results correspond to the normal DPCM.

From the results in the Table 1 it can be seen that as the m increases and the compression time decreases the compression ratio drops only slightly for small values of m (m=1..3). The same phenomenon can be observed from Figure 1 that shows the ratio between average compression ratios for different values of m and normal DPCM (m=1). Figure 2 illustrates the compression time in similar fashion.

Table 1. Average results for the 10 HES images.

m	**CR**	**time [s]**
1	2.193	530
2	2.189	259
3	2.183	217
4	2.177	212
5	2.169	203

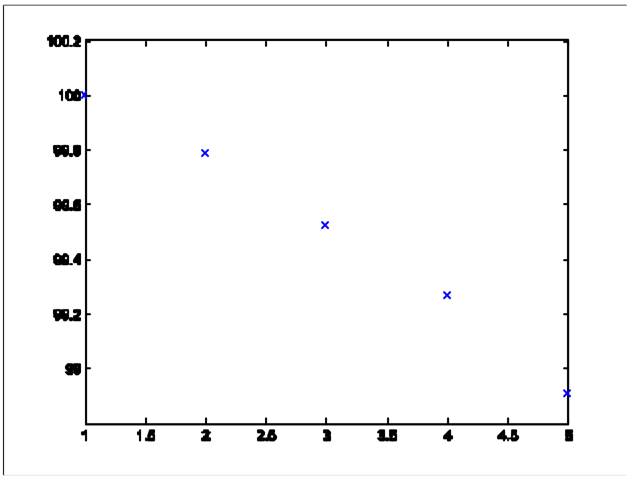

Figure 1. Percentage of the compression ratio compared to the normal DPCM as a function of "m".

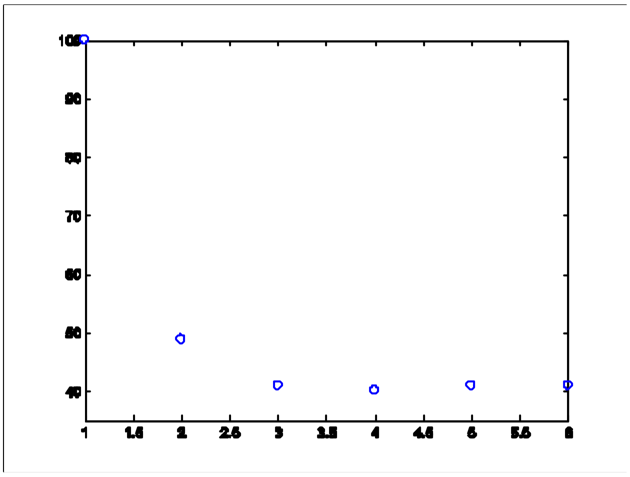

Figure 2. Percentage of the compression time compared to the normal DPCM as a function of "m".

5 Conclusions

The spectral DPCM method is responsible for the best compression ratios known today for hyperspectral sounder images. The spectral prediction procedure is rather time consuming and for this reason we have modified our original spectral DPCM method. The compression ratio remains almost the same with our modified method, at the same time the compression time is reduced to the half of the original compression time.

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