Hyperspectral Data Compression Framework for Earth Remote Sensing Objectives

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Abstract. The hyperspectral data compression framework to well investigate various compression models is presented. Results received with arithmetic encoder, context-adaptive QM-encoder, adaptive Huffman encoder are adduced. As a test data the Maine frame set from the AVIRIS freely available data was used. The received results testify the efficiency of the proposed framework in comparison with some alternative lossless compression algorithms.

Keywords: Hyperspectral data · Fourier Transform Imaging Spectrometer · Arithmetic coding · Context-adaptive QM-encoder · Adaptive Huffman encoder · AVIRIS

1 Introduction

Remote sensing is a method of acquisition of information about objects or areas without making physical contact with them. To acquire information, the specialized film-equipment is mounted on board of the satellite or the plane, flying over the target area. The equipment fixes reflected radiation from Earth surface in various spectral bands, and then converts it into digital form for transmission obtained data to the processing station.

Operating range of wavelengths of the remote sensing process is determined by specific problem facing the mission. There are systems dealing with radiation from micrometers (visible optical) to meters (radio wave). Multispectral systems usually operate within several non-overlapped spectral bands while hyperspectral ones treat with hundreds adjacent narrow bands.

Depending on the type of orbital sensor there are distinguished multispectral (e.g., Landsat, IKONOS, Rapid Eye, etc.) and hyperspectral (e.g., AVIRIS) ones. The main difference between them are the number of bands and their location order over spectrum. A multispectral sensors cover the spectrum from the visible up to the longwave infrared. They do not provide the continuous spectral range of an object but some discrete regions. Unlike these hyperspectral sensors deal with narrow spectral bands over a continuous spectral range, and produce the real spectrum of all pixels in the scene. So a sensor with 20 bands can be both hyperspectral when it densely covers whole range and multispectral when its bands did not adjoin.

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2 Trends in Remote Sensing System Progress

Trends in the evolution of remote sensing systems show that the emphasis is shifted to hyperspectral direction. However, the wide practical use of aerospace monitoring on the one hand hampered by the lack of sufficient number of satellites and aircraft equipped with appropriate spectrometers, and on the other hand there are difficulties associated with transmission, processing and interpretation of large amount of data generated by these devices.

Traditional data representation (classic hypercube) transmitted to the processing center are three-dimensional cube (Fig. 1) with the following resolution characteristics:

- spatial which determines the underlying surface details;
- spectral which determines width of spectral band;
- radiometric which determines number of signal levels that the sensor can register.

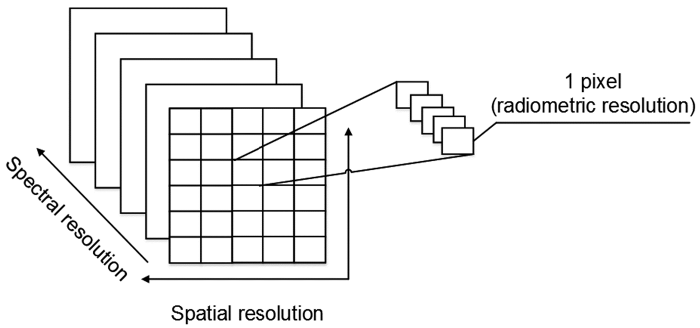

Fig. 1. Remote sensing data structure

The structure leads to need to transmit a huge data volume from orbit to the Earth and the problem of data compression becomes very acute and comes to the edge of technology. For example, volume of the AVIRIS [1] data sets which are used for compression algorithms and software research and development has following characteristics – 680 columns width (for AVIRIS Maine), 224 spectral samples per pixel, 12 bits per sample. This leads to more than 223 kB data per row to be transmitted over radio link. Taking into account the characteristics of modern radio links and the fact that the scanning is carried out in continuous mode the primary requirements to data compression algorithms are high compression ratio and low computation complexity. The last is concerned with limited onboard hardware capabilities.

3 Fourier Transform Image Spectrometer

There are some approaches to form the hyperspectral response for single pixel of image. Classical solution is using the prism or diffraction grating with swinging mirror scanning along row and orbital movement as column directions. Particular kind of hyperspectral equipment is the Fourier Transform Imaging Spectrometer (FTIS) based on any interferometer, for example, Sagnac one [2] (Fig. 2). Unlike equipment fulfilling direct spectral measurements FTIS outcome is interferogram that requires special processing to obtain the same spectral image cube with dimensions equal to rows × cols × spectral response. That special processing is one of Fourier transforms, e.g. cosine one. There are two approaches – to transmit raw FTIS data over radio link and fulfill Fourier transform on receiver side, and fulfill Fourier transform onboard and transmit ready spectral data. Our work with respect to FTIS deal with the first case – raw data are compressed and transmitted; all remaining work is fulfilled by receiver.

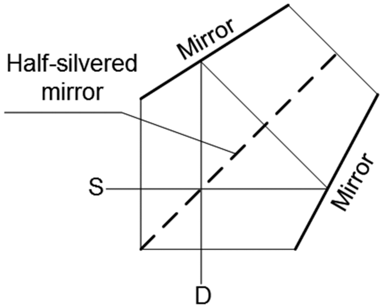

Fig. 2. Sagnac interferometer

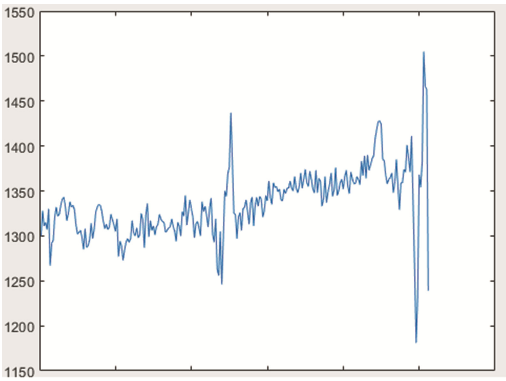

Fig. 3. Modulation function sample

To test the compression algorithms some technique of synthesis of Fourier interferograms from AVIRIS hyperspectral data has been developed. Modulation function shown in Fig. 3 is formed on the basis of real data or is synthesized mathematically:

$$u_{i,j}^{k} = \frac{v_{i,j}^{k} \cdot m_k}{v_{\max}^{k} \cdot m_{\max}} \tag{1}$$

where $u_{i,j}^{k}$ and $v_{i,j}^{k}$ – value in a layer k of pixel (i,j) of the initial and modulated cubes, respectively; $v_{\max}^{k}$ – the maximum value in a layer k ; m_k – the maximum element in a layer k ; $m_{\max}$ – maximum element of all cube. The received value is rounded up to closest integer number.

4 Review of Compression Algorithms

After analysis of the literature following two classes of hyperspectral data compression algorithms have been identified:

- using commonly known compression techniques;
- using adaptation under their given condition.

The first class of compression algorithms are often uses lossless and near lossless methods. Algorithm compresses near lossless if the information loss does not exceed the noise induced by the equipment used (spectrometer). As part of this approach are the following basic classes:

- algorithms based on prediction (LP [3], FL [4], SLSQ [5], CCAP [6], M-CALIC [7]);
- algorithms based on table look-up (LUT [8], LAIS-QLUT [9]);
- algorithms based on wavelet decomposition (3D-SPECK [10]).

The compression algorithms based on prediction outline some area in the vicinity of the pixel within which the mathematical operation is performed (the prediction step). The result of the prediction is subtracted from the original pixel value and the prediction error is generated, which is transmitted to the entropy coding unit. The output of that unit form is compressed data stream. Decompression is carried out in reverse order. As a coding system, for example, the Golomb-Rice codec may be used or any arithmetic one allowing hardware implementation.

The main problem of many prediction algorithms is high computing complexity. But algorithms need low memory requirements.

The objective of look-up table algorithms is speed up the computations using the fact that the correlation between the spectral channels is essential enough. For this purpose, the table containing the prediction values is used. The dimension of that table is equal to number of spectral channels multiplied by the maximum value for the given radiometric resolution.

The prediction process for current `sample[row][col][layer]` is:

```
pred[row][col][plane] =
LUT[layer][data[row][col][plane-1]];
LUT[layer][data[row][col][plane-1]] =
data[row][col][plane];
```

where plane is spectral channel index. The resulting value `pred` will be considered as predicted. Further processing is equivalent to the prediction algorithm.

The algorithms based on the discrete wavelet transform is the most demanding to computing resources. This class of algorithms requires to preliminary transform every spectral plane to the spatial frequency domain. Then first are encoded the most significant (high-frequency) of the wavelet coefficients and the least significant ones are coded in the last.

This approach allows both lossless (when all the wavelet coefficients are encoded), and controlled lossy compression. The main drawback of the approach is the computational complexity associated with the data cube transformation to the frequency domain, as well as requirements to memory bandwidth because will be random memory access when processing wavelet coefficients.

The other approach is based on an essential redundancy of the generated data that is caused by high spectral resolution. The algorithms of the class are based on the following simplifications:

- requirements to necessary spectral characteristics are known. In this case it is possible to transmit only necessary spectral channels or do not transmit uninformative ones (which could occur, for example, due to bad atmospheric condition), i.e. reduce the hyperspectral case to multispectral one;
- perform a full or a partial analysis of received data and transmit the result, but not the data itself. Unfortunately, this approach is difficult to implement on satellite board. Nevertheless, the advantage of approach is that the required data transmitted to the Earth.

5 Features of Hyperspectral Data

When designing the compression algorithm some correlation characteristics of hyperspectral data was studied allowing to evaluate the similarity between pixels and channels. The following formula are used to determine the spectral (2) and the spatial (3) correlation [11]:

$$c_{u,v} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} \tilde{x}_{i,j,u} \cdot \tilde{x}_{i,j,v}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} \tilde{x}_{i,j,u}^2 \cdot \sum_{i=1}^{M}\sum_{j=1}^{N} \tilde{x}_{i,j,v}^2}} \tag{2}$$

$$c_k(i,j) = \frac{C(i,j)}{\sqrt{C(i,i) \cdot C(j,j)}} \tag{3}$$

where $\tilde{x}_{i,j,k} = x_{i,j,k} - \bar{x}_k, x_{i,j,k}$ – value of pixel with coordinates (i,j) in the spatial slice of the channel k, $\bar{x}_k$ – a population mean in the channel k, M and N – width and height of the channel in spatial area, $C = \mathrm{cov}(X)$ – covariance matrix.

As can be seen from Figs. 4 and 5, the correlation between closely spaced interferogram tends to one. However, there are areas the correlation between which tends to zero. This is the result of weather condition, for example, part of the far infrared radiation is absorbed by water vapor and carbon dioxide. Respectively if the spectrometer covers the appropriate range of spectrum some notches may be occur on spectrogram.

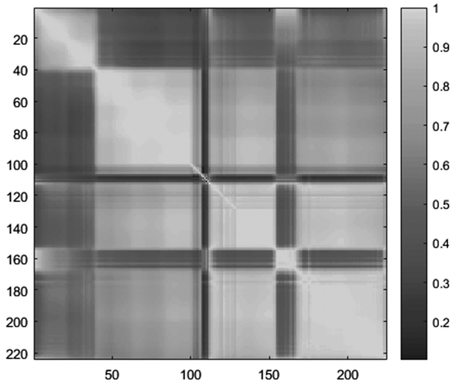

Fig. 4. Spectral correlation

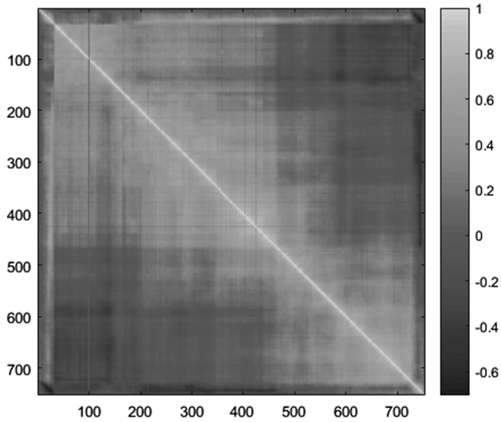

Fig. 5. Spatial correlation

The main requirements for the compression algorithm are:

- universality that means possibility of using the traditional spectral hypercube and Fourier-interferogram formed one;
- lossless compression that is caused by insufficient information available related to influence of data loss on the quality of the interferogram hypercube recovery;
- computational simplicity of the algorithm and the possibility of parallel processing.

6 Hyperspectral Data Compression Framework

In accordance with aforementioned features and requirements compression algorithm has been developed. That algorithm consists of preprocessing of each interferogram sample plane, reduction of correlation degree between the interferogram sample plane, and an encoder.

Figure 6 shows an example for three interferogram sample planes. The total number of sample planes is divided into subset of fixed size $m < M$ which are input of a compression algorithm. Recommended $m = 10 - 15$ sample planes. This recommendation is related with correlation between the sample planes (Figs. 4 and 5).

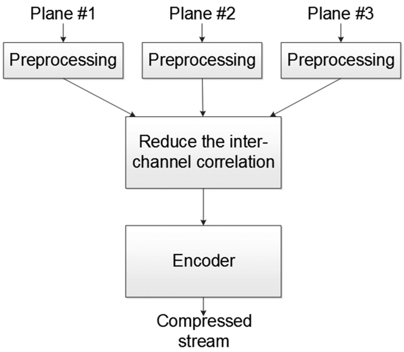

Fig. 6. Compression system model

As the preliminary step lossless wavelet decomposition is used. This allows to reduce data redundancy, and appends the ability to control the compression process (model adaptation for lossy compression case).

To reduce the degree of correlation between adjacent sample planes the difference method is used.

The final stage of the algorithm is the result encoder to compressed stream. The following options are examined as the encoder:

- adaptive Huffman encoder;
- arithmetic encoder;
- contextadaptive QM-encoder.

7 Framework Testing

AVIRIS (Hawaii, Maine) set was used to test compression model. AVIRIS is a standard in the field of hyperspectral data compression research. The sensor allows to capture images with a spatial resolution of 20×20 m per pixel in the spectral region from 400 nm to 2500 nm. Channel bandwidth is equal to 10 nm (224 spectral channels). The sensor uses 12-bit analog-to-digital converter.

To form interferogram from AVIRIS hypercube data modulation method was used (1), the modulation function shown in Fig. 3.

Test data comply with the following parameters:

- radiometric resolution – 12-bit positive integer;
- spatial image resolution – 512 lines, 680 columns for AVIRIS Maine and 614 columns for AVIRIS Hawaii;
- number of spectral channels for classic hypercube – 224;
- number of interferogram sample planes generated – 256. (Table 1)

Table 1. Test results

	Compression ratio, times	
	AVIRIS Maine	AVIRIS Hawaii
Classic hypercube		
Arithmetic encoder	2,98	3,16
Context-adaptive QM-encoder	2,91	3,11
Adaptive Huffman encoder	3,02	3,21
Fourier interferogram		
Arithmetic encoder	4,69	4,62
Context-adaptive QM-encoder	4,50	4,55
Adaptive Huffman encoder	4,78	4,70

The advantages of the proposed compression algorithm are:

- universality – it is possible to apply algorithm to the classic hypercube and interferogram one;
- possibility of parallel processing;
- computational simplicity (there are no arithmetic operations with high latency, i.e. multiplication and division).

8 Conclusion

The received results testify the efficiency of the proposed framework in comparison with some alternative lossless compression algorithms. The offered operation sequence is mathematically simple and does not demand essential computing resources.

In prospect it is expected to:

- explore various versions of wavelet-decompositions;
- extend the test set by other AVIRIS, LANDSAT, and SPOT-4 data.

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