ON SELECTED METHODS FOR HYPERSPECTRAL DATA COMPRESSION

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ABSTRACT

The aim of this paper is to introduce the problems inherently associated with hyperspectral data compression and to outline a path towards a feasible hardware implementation. First of all, the conception of hyperspectral data is clarified together with some background technical details. Thereafter, brief review of broadly recognized methods for the data compression is given. These initial steps will enable the definition of an appropriate compression framework, which takes into account the specific nature of hyperspectral data. Recently published methods aptly illustrate the whole conception. Finally, the eventuality of a hardware implementation together with a perspective of future development is considered.

1. INTRODUCTION

Information processing has been playing a crucial role in modern age. It's nearly impossible to imagine everyday life with myriad of sophisticated electronic devices used for various tasks. However, during the course of time there appeared a major problem that is: how to cope with increasing amount of data due to requirements of quality, precision or reliability. It's necessary to realize that communication channels or available storage place can provide only limited capacity. That's why data compression has been recently one the most eminent research issues.

The practical implications, extending far beyond scientific community, are evidently indisputable. Rich variety of data compression techniques and principles were devised in order to fulfil manifold requirements in an application domain. However, careless exploitation of the major widespread schemes tends to exhibit insufficient performance traits in particular situations. Such unwanted effects become apparent, for example, with the increasing dimensionality of source data to be processed. This paper takes a look on such pitfalls within the context of hyperspectral data sets.

Let us note that purely intuitive extension of 1D or 2D methods for multidimensional purposes will lead to mismatch with background statistical characteristics in a new domain. In effect, lower visual quality of resulting image, low execution speed or exhaustion of available storage space may be encountered. The possible remedy may involve appropriate combination of relevant methods at hand or their respective changes. Unfortunately, specific constraints (resulting data size, processing complexity, computational speed, power demands, etc.) may not be easily satisfied in that way. Then, the other approach, which is connected with significant effort towards the development of brand-new strategy, comes onto the stage.

This article will briefly examine a choice of recently published schemes for hyperspectral data compression which are based on so-called spectral unmixing approach. From this point of view, common methods for data compression will be considered with the aim to further improve compression ratio while achieving very good visual quality. Subsequently, several ideas for hardware acceleration (typically with FPGA circuits) will be presented.

2. HYPERSPECTRAL DATA CHARACTERISTICS

The continuous technological advancements in the area of electronics have enabled sophisticated electro-optical remote sensing devices generally known as imagining spectrometers. Hyperspectral sensors are recognized as one type of such devices. Main reason behind their deployment is the effort to obtain continuous spectrum of electromagnetic radiation being reflected form the surface of the Earth. In fact, hyperspectral image resemble a 3D data cube which consists of contiguous 2D slices (specified by X and Y dimensions) in different frequency bands (the third dimension). The actual data values are the intensity of the light at one wavelength from the particular location on Earth.

Now, let's support the idea of hyperspectral data processing by examples of possible applications. Due to the nature of such kind of data the perspective application scenarios may include mineral exploration, environment monitoring, urban planning or military surveillance. Because hyperspectral data are picked up in a large scale manner, it's possible to identify and to distinguish between spectrally similar materials (vegetation, for example).

Most of the imaging spectrometers are carried onboard air-borne platforms. One prominent example is NASA's Airborne Visible Infra Red Imaging Spectrometer (AVIRIS) [1]. It produces 224 spectral bands with wavelengths ranging from 400 to 2500 nanometers in resolution 20 x 20 meters per pixel. The output of spectrometer is scaled and rounded into resulting 16-bit integers. Each of such images is stored as a block of 614 x 512 pixels. When the number of band increases there is always corresponding drop in spatial resolution. That is to say, most of the pixels are mixed with contribution from surrounding pixels.

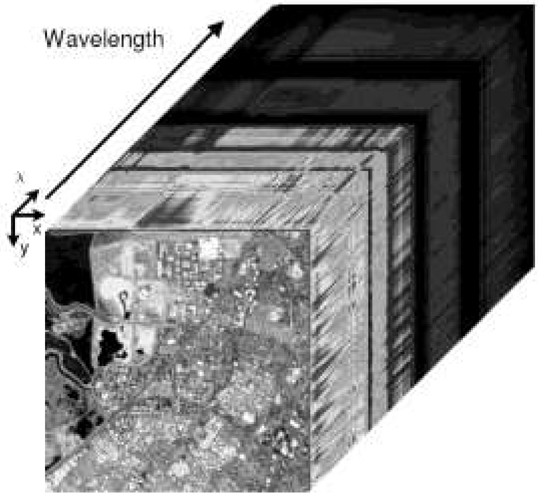

Figure 1: An example of hyperspectral data representation in a form of a 3D cube [1].

3. BASIC PRINCIPLES AND METHODS

The tremendous amount of data generated during hyperspectral sensing evidently demands suitable method of compression just to allow a convenient handling of the information. Technically speaking, compression is nothing else than the best approximation of the original data set. Different methods primarily focus on minimizing the correlation among individual elements (pixels, in our case) and thus get rid of a constituent redundancy. This approach helps to achieve better compression rate.

Based on the requirements imposed by accuracy or available storage resources, the chosen compression procedure can follow lossless or lossy direction. Typical compression flow consists of several stages: correlation removal, information redundancy modelling and entropy coding. Correlation removal is carried out by transform coding or prediction of pixel values. When specific level of degradation is acceptable, transform or prediction coefficients may be adequately scaled. The whole process ends up with application of suitable entropy coding scheme, like Huffman or Arithmetic coder, followed by data delivery.

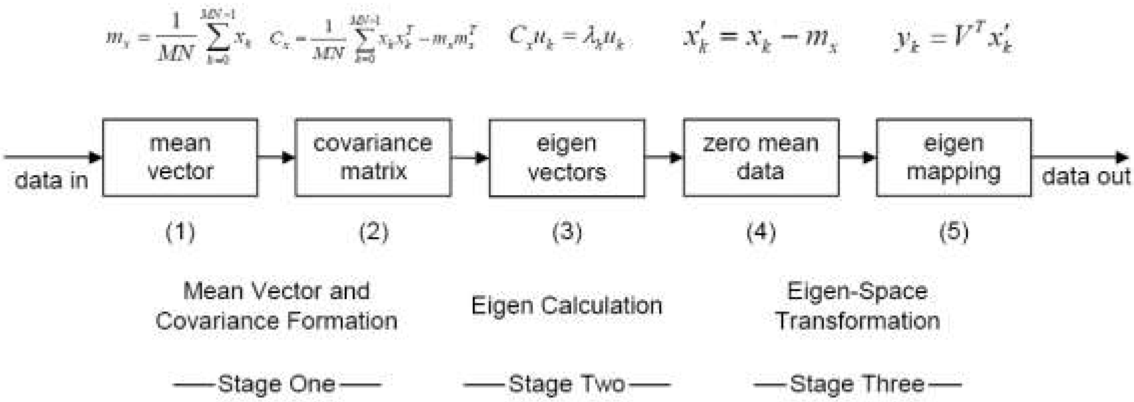

Figure 2: Illustration of Karhunen-Loeve transform computation.

Compression suits, which have been devised for hyperspectral data sets, are mostly governed by the computation flow suggested above. Many of these techniques exploit spatial and spectral correlation with subsequent entropy coding. Popular examples include variants of DWT transform [1] together with set of partitioning methods such as SPITH and its variations (SPITH-2D, SPITH-3D, SPECK). Moreover, other approach may involve combination of one-dimensional spectral decorrelator, such as Karhunen-Loeve transform (KTL) with optimal energy compaction (see Figure 2), and spatial domain methods, mostly variants of DWT or even JPEG2000 [1]. In particular situations the results can be improved by spectral bands ordering according to their mutual correlation (1).

$$r_{A,B} = \frac{\sum_{j=0}^{\frac{M}{D}} \sum_{i=0}^{\frac{N}{D}} \left(A_{j\cdot D,i\cdot D} - \bar{A}\right)\left(B_{j\cdot D,i\cdot D} - \bar{B}\right)}{\sqrt{\sum_{j=0}^{\frac{M}{D}} \sum_{i=0}^{\frac{N}{D}} \left(A_{j\cdot D,i\cdot D} - \bar{A}\right)^2 \sum_{j=0}^{\frac{M}{D}} \sum_{i=0}^{\frac{N}{D}} \left(B_{j\cdot D,i\cdot D} - \bar{B}\right)^2}} \tag{1}$$

4. SPECTRAL UNMIXING APPROACH

The significant computational demands behind optimal transforms like KLT have been recently addressed by the introduction of spectral unmixing techniques. Spectral imaging sensors often record scenes in which numerous disparate material substances contribute to spectrum measured from a single pixel. Spectral unmixing is the procedure by which the measured spectrum of a single pixel can be decomposed into collection of constituent spectra (endmembers) and a set of corresponding fractions (abundances), that indicates the proportion of each endmember present in the given pixel.

Spectral unmixing is usually performed by means of a linear mixture modelling approach. In mixture modelling the spectral signature of each pixel vector is assumed to be a linear combination of a limited set of fundamental spectral components – endmembers. Hence, spectral unmixing can be formally defined in equation (2):

$$\vec{x} = \sum_{i=}^{M} \vec{e}_i + \vec{v} = \vec{E}\bar{a} + \vec{v}, \tag{2}$$

where **x** is the d-dimension received pixel spectrum vector, **E** is the *d x M* matrix whose columns are the d-dimension endmembers $\boldsymbol{e}_i$, $i=1,\dots, M$, **a** is the M-dimension fractional abundance vector, and **w** is the d-dimension additive noise observation vector. The linear mixing model is subjected to two constraints on the abundance coefficients. Firstly, just to ensure physical meaning, all abundance coefficients must be non-negative $a_i \geq 0$, $i=1,\dots, M$. Secondly, to account for entire composition, they must be additive, ie. sum of all $a_i = 1$. After the creation of abundance images these will be fed through the entropy coding stage.

4.1. SELECTED METHODS FOR SPECTRAL UNMIXING COMPRESSION

Pixel Purity Index [2] – This algorithm (PPI) requires a known number of endmembers and will find spectral signatures from the input hyperspectral data cube. In the N-D space, a line (skewer vector) is generated randomly and each observation of **x** is projected onto the this line. The purity index is incremented for a given **x** when their projections are located at the extremum of the overall projection point. This process may be iterated several times according to the required number of endmembers.

Automated Morphological Endmember Extraction [3] – The process of endmember estimation is performed locally through sliding window of increasing size. This procedure profits from the selective sensitivity to noise of of the Associative Morphological Memories (AMM) for the detection of the morphological independence conditions that are necessary constraint of endmember spectra. This procedure is unsupervised and doesn't need an explicit setting of the number of endmember to search for. In fact, AMM's are the morphological counterpart of the well known Hopfield Associative Memories. The process of searching for endmembers involves maximum and/or minimum operators within region of search space, which is defined by a set of morphologically independent vectors in both erosive and dilative sense.

Particle Swarm Optimization [4] – This interesting approach to the problem for a determination of endmembers takes its inspiration from social behaviour of bird flocks. PSO is generally considered to be an evolutionary computation paradigm. It belongs to the class of algorithms which simulate biological evolution and are population-based. In a PSO system, a swarm of individuals, that may be called particles, fly through the search space. Each particle then represents a candidate solution to the problem.

5. ASSUMPTIONS FOR HARDWARE REALIZATION

The implementation or acceleration of compression methods purely in hardware has a perfect sense in situation when significant speedup can be achieved. It’s possible to address such implications, for example, with systolic array platform (see Figure 3) which can be transparently mapped onto the structure of FPGA-like circuits. As it is shown, spectral unmixing and endmember determination is extensively parallelized.

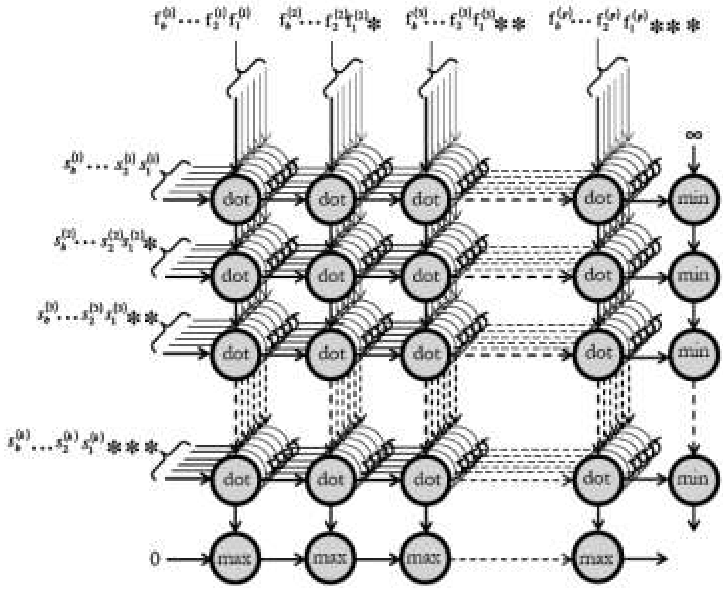

Figure 3: Endmember selection method realized in a form of systolic array.

6. CONCLUSION AND FUTURE WORK

We expect that our future fork will be directed towards non-conventional methods of hyperspectral compression. These include methods suggested in (4.1) but our main concern is primarily tied with an efficient hardware realization. Computational structure like systolic arrays or cellular automata may be a good deal with acceleration in FPGA.

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