A Simple Lossless Algorithm (SLA) for on-board Satellite Hyperspectral Data Compression

Vijay Joshi $^1$ and Sheeba Rani J $^2$

$^1$Indian Institute of Space Science and Technology
$^2$Affiliation not available

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Abstract

A novel algorithm for on-board satellite hyperspectral data compression is proposed. Computational complexity is targeted with comparable compression performance with state-of-the-art on-board satellite hyperspectral data compression methods.
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Vijay Joshi, Sheeba Rani J, Senior Member, IEEE

Abstract—As resolution of on-board imaging spectrometer keeps improving, data acquisition rate increases and resource limited satellite environment necessitates for computationally simple data compression method to meet time, bandwidth and resource requirements with error resilience. This paper proposes a new lossless, prediction based algorithm for on-board satellite hyperspectral data that utilizes spectral as well as spatial correlation and at the same time is computationally less complex. Combination of nearest neighbor and non-binary tree traversal method with neighbor driven decision making is used in preprocessing stage. Extended causal neighborhood of current sample is used to minimize the prediction residual, which makes more than 80% calculations causal in nature. The prediction residual is then encoded using sample adaptive Golomb coding. CCSDS corpus of data for hyperspectral images is used for evaluating the performance of algorithm and comparison of data rates with state-of-the-art on-board lossless compression methods shows good results. Further, it shows reduced computational complexity and high error resilience in comparison to other methods.

Index Terms—Lossless compression, Satellite data compression, Hyperspectral data compression, Neighbor driven decision making.

I. INTRODUCTION

Due to limited downlink bandwidth and on-board storage capabilities, large amount of data from high resolution imaging sensors needs to be compressed on-board before transmission to earth station. However, the limited resources available on the payload poses challenges on the on-board codecs because of its computational intensive task and high input data rates from the sensor. Basic building blocks of conventional satellite imaging system are imaging sensor, analog to digital converter, radiometric corrector, image compression, entropy coding and RF module for transmission to earth station [1, 2]. Remote sensing satellites in low earth orbit (LEO) and geostationary earth orbit (GEO) are placed to provide images for research, agriculture, forestry, environmental mapping, land cover and other atmosphere monitoring applications. Space-borne imaging offers large coverage area, repetitive coverage of area of interest, which provides quantitative measurement of ground features. In case of earth orbital and outer space mission, outer space condition put a check on computational complexity, efficiency of compression method and error resilience [3].

Based on frequency of sensing or number of bands captured, satellite images can be divided into three types viz. panchromatic, multi-spectral (MSI) and hyper-spectral (HSI). Panchromatic images are black and white images, whereas multi-spectral images consist of multiple discrete frequency bands in visible and IR region. Hyper-spectral images have hundreds of contiguous bands, that contain large amount of information [4]. Linear imaging self-scanning system (LISS), Quickbird and Spot are some MSI sensors deployed. Some HSI sensors are visible near Infrared (VNIR) on HySIS, HySI (Hyper Spectral Imager), LiVHySI (Limb Viewing Hyper Spectral Imager), etc. As more number of overlapping bands are present in HSI, more correlation is found and can be used for compression [5].

On-board image compression started with SPOT 1 satellite using differential pulse code modulation (DPCM) followed by fixed length coding [6]. Same method continued till SPOT 4. Discrete cosine transform (DCT) based methods were used with scalar quantization and fixed length coding. DCT based compression with variable length coding was used after this, which is very close to JPEG standards, which were defined later. A simple method for lossless compression using look up table (LUT) uses causal method along with LUT to speed up the process [7]. First, co-located pixel value is searched in previous band in reverse raster scan order and nearest neighbor (NN) is selected. Corresponding value in current band is the prediction of sample. All pixels and predicted values are stored in form of a look up table. The algorithm is suitable for compression of hyper-spectral image data in the band-interleaved-by-line (BIL) format. It uses LUT for prediction, thus less complex implementation, but memory requirements are very high and since there is search for NN, timing requirements are also high. To improve prediction of simple LUT based method, a predictor selection mechanism also used with LUT [8]. A locally averaged inter-band scaling (LAIS) factor is calculated for an estimate of current pixel from the co-located pixels in previous band. Memory requirements and complexity of system are increased as LIAS calculation and storage is additional in comparison to previous method. Distributed source coding (DSC) based method is used to improve error resilience by using 16*16 blocks and reduce computational complexity as it uses less number of operations (additions and multiplications) in comparison to other methods [9].
HSI or 3-D images can also be seen like video signal, thus video compression standards are applied for on-board compression [10]. H.264/AVC video coding standard is applied for lossy image compression to improve compression ratio. This work shows compatibility of video compression standards for on-board compression, but because of pre-processing and unmixing, complexity increases. A lossless algorithm based on adaptive filter shows improved bit rates and reduced complexity. For prediction, local mean is calculated first using neighboring pixels, possible in two modes viz. full prediction and reduced prediction mode. It’s called Fast Lossless (FL) algorithm and is faster, accurate and less complex in comparison to previous methods used for on-board compression [11]. Consultative Committee for Space Data Systems (CCSDS) developed 123 standards for lossless image compression after reviewing all lossless existing image compression methods [12]. CCSDS 123 uses only positive integers and extends fast lossless method. CCSDS provides best compression performance among existing methods, but is computationally complex [13].

It’s observed that in all previous on-board lossless compression methods, there is a tradeoff among computational complexity, error resilience, compression performance and effective use of spectral correlation in hyperspectral images. Thus, to balance above aspects with target of achieving least computational complexity with high error resilience, a simple lossless algorithm for on-board satellite hyperspectral data compression (SLA) is proposed, which uses spectral as well as spatial correlation. Concepts of NN, tree traversal with neighbor driven decision making are incorporated to achieve compression. Use of NN method in pre-processing stage of compression methods can be seen previously, but it is used with extensive search operation in spectral or spatial neighborhood and in turn increases timing requirements and number of operations. This paper proposes neighbor driven decision making combined with NN and tree traversal, thus eliminating need of extensive search for NN.

Rest of the paper is organized as follows. Next section talks about proposed algorithm, section III talks about experimental results, section IV concludes the present work with future work and directions.

II. PROPOSED METHOD

A. Problem perspectives

Lossless compression can be seen as combination of source encoder and entropy encoder [13]. In source encoder or pre-processing stage, correlation in hyperspectral images is utilized to predict value of present pixel and get prediction residual, which is then encoded for transmission.

One possible way of approaching lossless image compression is using NN and non-binary tree traversal with three stages S1, S2 and S3 is shown in fig.1. In first perspective of NN, difference between current pixel and NN (either spatial or spectral neighbor) is calculated and called as local difference (LD). In second stage (S2), LD is processed with minimization factors, which are pre-computed based on previously processed samples i.e. causal pixels. For further minimization in third stage (S3), this minimized LD is operated with smoothing factors, that are derived from minimization factors and prediction residual for the current pixel is achieved as shown in fig.1(a). In second approach of non-binary tree traversal, spatial as well as spectral LDs of present sample are calculated in S1. In second stage (S2), pre-computed factors are used for minimization and finally this minimized value is operated with smoothing factors to get prediction residual in S3, as shown in fig.1(b).

These approaches of image compression are computationally simpler than other state-of-the-art methods, however real time implementation is challenging as selection of appropriate neighbor in NN method and selecting optimal path in tree traversal demands more side information. Thus, to reduce the side information requirement for selecting appropriate neighbor and path, SLA proposes a neighbor driven decision making, which helps in selecting appropriate neighbor or path.

![Fig. 1. Use of three stage (a) NN and (b) non-binary tree traversal perspective of image compression with local difference (S1), minimization factors (S2) and smoothing factors (S3) for image compression.](image-url)
B. SLA

Block diagram of SLA is shown in fig. 2. Previously processed pixels i.e. causal pixels undergo generation and selection stages of LD and factors for decision making, which is inspired by tree-traversal problem, whereas processing of current pixel reflects NN approach. Block diagram is explained below:

i) Pre-computations: Before arrival of current pixel, pre-computations start using causal pixels, which are used to compute wide neighborhood local sum (WNLS). Fig. 3 shows neighborhood of current pixel. WNLS is used to calculate minimization factors in factor selection and generation stage. WNLS is calculated same as in [13] and minimization factors are of two types viz. spatial and spectral factors. Spatial factor is the difference of average WNLS and causal neighbor. Similarly, spectral factor is the difference of collocated pixel of present pixel in previous band i.e. $S_{z-1}(y,x)$ and causal neighbor. Four type of spatial and spectral factors are there corresponding to north, west, north-west, north-east neighbors respectively. Reverse spectral factor is the difference of average WNLS and collocated pixel of current pixel in previous band. Minimum factor out of four spatial and spectral factors along with reverse spectral factor is used to calculate smoothing factors.

ii) Local difference generation and selection: Current pixel and average WNLS are used in this stage to generate local difference of two types viz. spatial and spectral. Spatial LD is the difference of current pixel and causal neighbor. Five type of spatial LD are there corresponding to north, west, north-west, north-east neighbor, average WNLS respectively. Similarly, spectral LD is the difference of current pixel and collocated pixel of current pixel in previous band. The neighbor driven decision making approach is used to select LD based on mode of the algorithm, which is given in subsequent sections.

iii) LD minimization: In this stage, LD of current pixel is processed with pre-computed and selected factor. First, difference between LD and selected minimization factor is taken and this difference is further subtracted with smoothing factor. Result of this stage is prediction residual, which is then sent for encoding and finally compressed bit stream is generated.

iv) Mapping function: SLA uses subtraction while generating and minimizing LD, thus to make it a positive integer based method, a mapping function is applied after every stage of
subtraction. For a variable \( a \), mapping function is shown in (1):
\[
M(a) = \begin{cases} 
2a & a \geq 0 \\
2|a| - 1 & a < 0
\end{cases}
\] (1)

C. SLA Modes and neighbor driven decision making

The proposed method operates in full and reduced mode based on the number of minimization steps in LD minimization stage. In full mode, both minimization and smoothing factors are used, while in reduced mode, only smoothing factors are used as shown in fig. 4.

SLA utilizes correlation in data cube by defining directional modes in full and reduced mode. This is based on the type of neighbor used in decision making for LD and factor selection. Four directional modes are defined, which are west, north, spectral and four causal neighbor mode. For example, in directional west mode, its assumed that there is a prevalent west neighbor correlation in data and already processed west neighbor is put through minimization steps. This assumption of prevalent correlation is verified by analysis of pre-processing stage in next section. The type of LD and factor that gives minimum value of prediction residual for west neighbor, is used for current pixel also. Similarly, directional north and directional spectral mode work. In case of absence of prevalent correlation, four causal neighbor mode is used, which uses west, north, north-west and north-east neighbors for decision making. Majority rule is used here and the type of LD and factor, which gives minimum prediction residual and is in majority among the four neighbors, is used for current pixel.

As the proposed algorithm has the flexibility of selecting modes, it provides a tradeoff among computational complexity, resources utilization and compression performance, which is shown in subsequent sections.

III. EXPERIMENTS AND ANALYSIS

CCSDS corpus of hyperspectral data is used to evaluate performance of SLA. MATLAB 2018Rb is used to perform software implementation of the algorithm on Intel(R)Xeon(R)W-2145 CPU with 3.75GHz and 128GB RAM. Analysis of pre-processing as well as complete compression flow is shown below. The detailed analysis of the proposed pre-processing stage is evaluated using cumulative probability distribution and complete compression flow analysis is analyzed based on computational complexity, compression performance in terms of data rates and error resilience are discussed.

A. Analysis of pre-processing stage

Pre-processing analysis of algorithm is done for studying entropy of prediction residual, which helps in selecting

<table>
<thead>
<tr>
<th>Instrument</th>
<th>SLA</th>
<th>JPEG-LS</th>
<th>JPEG-2000</th>
<th>ESA+</th>
<th>LUT+</th>
<th>CCSDS-122.0.B</th>
<th>CCSDS-123.0.B</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIRS</td>
<td>6.41</td>
<td>6.35</td>
<td>6.62</td>
<td>4.68</td>
<td>5.66</td>
<td>6.86</td>
<td>4.30</td>
</tr>
<tr>
<td>CRISM</td>
<td>5.57</td>
<td>5.53</td>
<td>5.97</td>
<td>8.92</td>
<td>9.54</td>
<td>6.92</td>
<td>5.06</td>
</tr>
<tr>
<td>M3-Target</td>
<td>4.23</td>
<td>3.66</td>
<td>4.00</td>
<td>6.60</td>
<td>7.44</td>
<td>5.02</td>
<td>3.09</td>
</tr>
<tr>
<td>SFSI</td>
<td>5.17</td>
<td>4.75</td>
<td>4.65</td>
<td>4.91</td>
<td>5.43</td>
<td>5.30</td>
<td>4.67</td>
</tr>
<tr>
<td>CASI</td>
<td>7.42</td>
<td>6.77</td>
<td>6.97</td>
<td>5.10</td>
<td>5.65</td>
<td>7.02</td>
<td>5.02</td>
</tr>
<tr>
<td>Hyperion</td>
<td>6.16</td>
<td>5.02</td>
<td>5.14</td>
<td>5.52</td>
<td>7.44</td>
<td>5.58</td>
<td>4.30</td>
</tr>
</tbody>
</table>
directional mode for a particular dataset. Initial results are evaluated using cumulative probability distribution of prediction residual. Log likelihood of exponential distribution is taken for comparison and mean value of exponential fit is compared among modes of the algorithm. It can be seen that prediction residual is limited near to mean of the exponential fit as shown in fig. 5 for AIRS dataset, thus reducing entropy of prediction residual. Table I shows directional mode selection and its observed that same directional mode of SLA pre-processing performs best for a particular instrument as there is predominance of portions of similar nature of correlation in dataset captured by an instrument. Full and reduced mode of operation for a particular directional mode can be selected as per resource availability as they use similar correlation.

B. Compression performance

Data rate (bps) is used for comparing compression performance with existing lossless hyperspectral compression methods as shown in table II. SLA performs at par with existing methods other than CCSDS 123 standards, which have high performance courtesy its intensive computations. Fig. 6 shows performance among all modes of SLA for some datasets from AIRS, M3, CASI and SFSI instruments. Further, it can be seen that when there is a specific prevalent correlation in dataset, its effectively utilized by SLA, otherwise as in case of SFSI, all modes show almost similar compression performance.

C. Computation complexity and error resilience

Computational complexity is measured here in terms of number of operations for a pixel. In case of west, north and spectral directional modes, only one pixel is used for decision making, whereas in case of directional four causal neighbor mode, maximum number of operations are performed as four pixels are used for decision making. Further, full mode uses more number of operation due to factor minimization stage. In directional four causal neighbor mode in reduced mode, 86 subtractions and 5 shift operations required for one pixel, 6 subtractions and 3 shifts are to be performed on present pixel. Thus, present pixel undergoes 6.97% of total subtractions and 60% of total shift operations. In case of directional four causal neighbor mode in reduced mode, out of total 44 subtractions and 4 shifts, 4 subtractions and 2 shifts are performed on current pixel. In this case, present pixel undergoes 9.09% of total subtractions and 50% of total shift operations. Since, shift operations performed are very less in comparison to subtractions, their resultant weightage in total calculations is less and thus, approximately more than 80% calculations are performed with causal pixels.

Error resilience is the ability to limit effect of possible error encountered either while memory access or transmission [9]. Error while memory access is limited in SLA as only subtractions is used to select LD and factors and even if bits corrupted, there is possibility of selecting same or other LD or factor, which will affect compression performance only. Further, as in directional four causal neighbor mode uses four causal samples for decision making separately for each current pixel, error limiting ability is high. In case of other three modes, only one sample is used for decisions, thus limiting effect of possible error to one sample.

IV. Conclusion

In order to develop an algorithm for on-board satellite hyperspectral data compression with low complexity and error resilience, SLA is proposed using NN, non-binary tree traversal and neighbor driven decision making. Algorithm shows comparable compression performance with least computational complexity in all modes and ability of directional mode selection for an instrument makes it suitable for mode calibration before deployment with an instrument.

Further to enhance compression performance, there is possibility of training model for inter and intra-band selection of modes in SLA using the correlation in hyperspectral data, which can be verified by studying entropy for bps of all modes in algorithm. Error resilience while transmission can also be studied to further improve reliability in error prone space environment.

REFERENCES