USING CCSDS IMAGE COMPRESSION STANDARD FOR SAR RAW DATA COMPRESSION IN THE H2020 EO-ALERT PROJECT

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ABSTRACT

In this paper, we describe compression strategies currently under consideration in the H2020 EO-ALERT project. In particular, we investigate the performance of the CCSDS-123.0-B Issue 2 standard for image compression when used for the purpose of compression of synthetic aperture radar (SAR) raw data onboard of satellite systems.

INTRODUCTION

The aim of EO-ALERT is to propose the definition and development of the next-generation Earth observation (EO) data and processing chain, based on a novel flight segment architecture moving optimised key EO data processing elements from the ground segment to on-board the satellite. The objective is to address the need for increased throughput in EO data chain, delivering EO products to the end user with very low latency. In EO-ALERT, compression is performed for both optical and synthetic aperture radar (SAR) data types. This paper investigates the SAR data compression problem, attempting to apply to SAR raw data compression techniques typically employed for optical images.

SAR data is obtained by emitting high frequency pulses and sampling the in-phase and quadrature components on the generated echoes. These samples are complex numbers which must undergo a process called focusing to form an image which is interpretable by the eye. In case of SAR systems on airborne vehicles and satellites, this process is usually too computationally expensive and it cannot be executed on-board. For this reason in most cases the SAR data is compressed and transmitted raw, with no pre-processing.

The downside of this approach is that compressing SAR raw data presents a great challenge compared to compressing image data. This is because SAR data consists of complex samples with low correlation among each other. Furthermore, the compression algorithm must have a low complexity due to the hardware constraints of the satellite systems and the high rate of data acquisition.

Historically the most used algorithm and the de-facto standard in the field of raw SAR compression is the Block Adaptive Quantization (BAQ) algorithm [1]. This algorithm is built around the assumption that SAR raw data can be modeled as a complex random process, where the imaginary and real parts are independent Gaussian samples with a slowly varying standard deviation. The technique consists of partitioning the data into blocks, over which the data samples can be assumed stationary, followed by quantization of each data inside the block using a Max-Lloyd quantizer.

Several evolutions of this technique have been proposed throughout the years, such as Entropy Constrained Block Adaptive Quantization [2], Block Adaptive Vector Quantization [3], Flexible Block Adaptive Quantization [4]. All these methods improve the performance of BAQ at the price of increased complexity.

Most of these approaches only take advantage of the first-order statistics of the raw data; however, other techniques exist which try to exploit the correlation between the SAR raw data samples. For example, is possible to apply the concept of transform coding for the purpose of compression, using transforms such as the Fourier transform, discrete cosine transform [5] or wavelets [6], but usually these approaches are not adopted as, again, they are too computationally complex.

The Standard CCSDS 123.0-B (Issue 2) "Low-Complexity Lossless & Near-Lossless Multispectral & Hyperspectral Image Compression" describes an algorithm for the compression of multidimensional images on-board of satellites, and it is based on a DPCM-scheme followed by an entropic coder.
As the viability of this kind of algorithms for the purpose of compression of SAR captures was already acknowledged in papers such as [7], this paper has the objective to apply this new standard to SAR raw data, and assess its performance in terms of rate and distortion. The real and the imaginary parts of the SAR raw data were compressed separately using the CCSDS standard, and the performance obtained on a dataset of images on real-worlds scene captured by the SIR-C/X-SAR mission [8] are equal to, or better than, those obtained by the BAQ technique.

The success of this approach yields the great advantage of employing an algorithm that is suitable for onboard implementation, and that SAR data can be treated in the same way as the optical data without adding complexity to the architecture, using the same algorithm for both optical and SAR data types.

DATASET

The tests described in the paper were executed on raw data related to the SIR-C/X-SAR mission (see [8]). The X-SAR sensor operates in stripmap mode; it has a carrier frequency of about 9.6 GHz, and a bandwidth of about 19 MHz. For these scenes, the pulse repetition frequency is 1488 Hz, the duration of each pulse 40 µs, and the range sampling rate is about 22.5 MHz. The I and Q parts of the received raw signal are quantized on 6 (for the image Innsbruck) or 4 bpp (for images Jesolo and Matera) prior to storage and transmission to the ground segment.

EXPERIMENT OVERVIEW

Compression of normalized SAR raw data

The first test regards the compression of the SAR data after energy normalization *i.e.* adding a block-wise normalization stage similar to BAQ as preprocessing stage to the CCSDS standard. Following the assumption also used in BAQ compression that the real and imaginary parts of the data can be modeled as two independent Gaussian random processes with a slowly varying standard deviation, the data has been divided into blocks of 32x32 samples and normalized so that each block has unitary standard deviation. After the normalization the data was quantized on 16 bit in the interval between -4σ and 4σ. The real and imaginary part of the samples were compressed separately using the CCSDS 123.0 using the following parameters:

- Number of Bands per Prediction P = 3
- Register Size R (in bits) = 64
- Weight Resolution Ω = 19
- Weight update scaling exponent change interval $t_{inc} = 64$
- Initial weight update scaling exponent parameters $v_{min} = -1$
- Final weight update scaling exponent parameters $v_{max} = 3$
- Prediction mode Full Wide/Neighbour Oriented

- Sample representative parameters all set to 0
- Use of non-band dependent absolute error limit.
- Sample adaptive Encoder with the following parameters:
- Unary length limit $U_{max} = 18$
- Initial count exponent $\gamma_0 = 1$
- Accumulator Initialization Constant K = 3
- Rescaling Counter size $\gamma^* = 6$

For comparison the same data were compressed using standard BAQ normalized on 32x32 blocks. The performance in terms of SNR of the two algorithms was compared at the same rate for both algorithms. The rates chosen for the comparison were 2 bpp and 3 bpp. The results of the tests are shown in Tables 1, 2, 3 and 4.

Table 1 - Results on raw data quantized on 16 bit with rate 2 bpp

2 bit Norm	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR CCSDS Real	SNR CCSDS Imag
Innsbruck	5100	2.007	2.008	9.8481	9.8035	8.9919	9.1329
Jesolo	5900	1.996	1.995	8.8841	8.5045	8.5598	8.4063
Matera	5800	2.009	2.003	9.88	9.8461	8.008	9.7033

As shown in Tab. 1, using 2 bpp the obtained performances are comparable to those of BAQ but tend to be lower.

Table 2 - Results on raw data quantized on 16 bit with rate 3 bpp

3 bit Norm	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR CCSDS Real	SNR CCSDS Imag
Innsbruck	2400	3.001	3.001	15.4039	15.3034	15.5343	15.6767
Jesolo	2800	2.987	2.986	13.0329	12.7464	15.0281	14.8777
Matera	2800	2.979	2.985	14.5174	14.4831	14.8777	16.2203

As shown in Tab. 2, at 3 bpp the CCSDS algorithm obtains slightly better performance compared to BAQ with a greater gain for the Jesolo image. The test was repeated quantizing the normalized data samples on 8 bit obtaining very similar results (see Tab. 3 and 4).

Table 3 - Results on raw data quantized on 8 bit with rate 2 bpp

2 bit Norm	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR Real	SNR Imag
Innsbruck	20	1.972	1.971	9.8481	9.8035	8.7396	8.8859
Jesolo	22	2.024	2.022	8.8841	8.5045	8.7672	8.6147
Matera	22	2.01	2.014	9.88	9.8461	8.0696	9.7685

Table 4 - Results on raw data quantized on 8 bit with rate 3 bpp

3 bit Norm	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR Real	SNR Imag
Innsbruck	9	2.982	2.981	15.4039	15.3034	15.4159	15.5642
Jesolo	10	3.038	3.037	13.0329	12.7464	15.3874	15.2344
Matera	10	3.026	3.032	14.5174	14.4831	14.6999	16.5811

Compression of SAR raw data with no pre-processing

As a second experiment, it was attempted to use directly the SAR raw data, without normalizing it. Since the data are already composed of integers no further quantization is needed.

Table 5 - Results on raw data with rate 2 bpp

2 bit	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR Real	SNR Imag
Innsbruck	4	2.065	2.082	9.8481	9.8035	11.4928	11.3151
Jesolo	1	1.73	1.723	8.8841	8.5045	7.5489	7.3603
Matera	1	1.8	1.797	9.88	9.8461	10.449	10.4998

The dynamics of the input data ranges between 6 bpp (Innsbruck) and 4 bpp (for Jesolo and Matera). For this reason is not possible to approximate accurately the rate used for the BAQ compression using the absolute error limit of the CCSDS 123.0 standard as the rate decreases very rapidly to 1 bpp even at low absolute error limit values, and the value that gives the rate which is the nearest to the desired one can be not as accurate as it was before.

As can be seen in Tab. 5, at the rate of 2 bpp the CCSDS algorithms provides results for the Innsbruck and Jesolo images that are up to 2 dB better that those given by BAQ. An exception is the case of Jesolo, in which the performance is worse of about 1 dB. In this case the rate is quite far from 2 bpp.

Table 6 - Results on raw data with rate 3 bpp

2 bit	MAD	Rate Real	Rate Imag	SNR BAQ Real	SNR BAQ Imag	SNR Real	SNR Imag
Innsbruck	2	2.76	2.739	15.4039	15.3034	16.4663	16.2952
Jesolo	0	3.148	3.14	13.0329	12.7464	Inf	Inf
Matera	0	2.9	2.908	14.5174	14.4831	Inf	Inf

Using a rate of 3 bpp it is possible to compress the raw data for Jesolo and Matera losslessy and for the Innsbruck file there is a gain of 1 dB (see Tab. 6).

DISCUSSION AND CONCLUSIONS

We have found that the CCSDS 123.0-B (Issue 2) standard for SAR raw data compression is very advantageous as on satellites which capture both optical images and SAR data it would be possible to use the same algorithm to compress both types of data, instead of having to implement two different techniques. The standards provides compression performance on SAR raw data as good as good as or better than BAQ.

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