Onboard Data Compression of Synthetic Aperture Radar Data: Status and Prospects

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ABSTRACT

Synthetic aperture radar (SAR) instruments on spacecraft are capable of producing huge quantities of data. Onboard lossy data compression is commonly used to reduce the burden on the communication link. In this paper an overview is given of various SAR data compression techniques, along with an assessment of how much improvement is possible (and practical) and how to approach the problem of obtaining it.

Keywords: Data compression, synthetic aperture radar, SAR

1. INTRODUCTION

Synthetic aperture radar (SAR) instruments on spacecraft are capable of acquiring huge quantities of data. As a result, the available downlink rate and onboard storage capacity can be limiting factors in mission design for spacecraft with SAR instruments. This is true both for Earth-orbiting missions and missions to more distant targets such as Venus, Titan, and Europa. (Of course for missions beyond Earth orbit downlink rates are much lower and thus potentially much more limiting.) Typically spacecraft with SAR instruments use some form of data compression in order to reduce the storage size and/or downlink rate necessary to accommodate the SAR data. Our aim here is to give an overview of SAR data compression strategies that have been considered, and to assess the prospects for additional improvements.

2. SAR DATA

SAR instruments transmit a series of radar pulses and record the reflection from the target, which may be Earth or another planetary object. Each radar pulse illuminates a fairly wide area on the target, and the received reflection is the combined reflection from the whole illuminated area. In particular, the reflection will be spread out in time, as different portions of the illuminated area will be at different distances from the instrument (and thus have different round-trip light times). Different points in the illuminated area also produce different reflection strengths depending on surface properties and the angle of incidence. In any case, the system is designed in such a way that the returns from consecutive pulses will not (normally) overlap. The received reflection is sampled in time, and each sample is a complex value for which the real and complex components correspond to the (digitized) in-phase (I) and quadrature (Q) components of the received signal.

Thus, overall, raw SAR data is conceptually a two-dimensional array of complex numbers, where each row of the array correspond to the return from a specific transmitted pulse and the position of a sample in the row corresponds to a specific return time.

The complex SAR data samples may be modeled as a sum of the elementary phasor contributions from a large number of independent scatterers[1]

$$\sum_{k=1}^{N_s} a_k e^{j\phi_k}$$

where the a_k are the reflectance amplitudes and the ϕ_k the phase delay. The reflectance amplitudes and phase delays are well modeled as independent of one another, with the phase uniformly distributed on $[-\pi, \pi]$. The real and imaginary components of this signal (I and Q components) are extracted and digitized, typically to somewhere between 5 and 8 bits per sample using a linear quantizer. One can show these components have zero mean, identical variance, and are uncorrelated. Since N_s is very large, the components may be approximated as having a Gaussian distribution.

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3. DISTORTION METRICS

Raw SAR data is inherently noisy, and the amount of compression possible with lossless compression is very limited, so lossy compression has been relatively well accepted for SAR data. In order to compare lossy SAR compression algorithms, it is necessary to define a reasonable distortion metric.

Suppose $g(x,y)$ is an $N \times N$ image array, containing either the real or imaginary components of a raw data set, or containing a processed image, and suppose $f(x,y)$ is its reconstruction from compressed data. The root-mean-squared (RMS) distortion of the reconstruction is given by

$$e_{\mathrm{rms}} = \left(\frac{1}{N^2} \sum_x \sum_y (g(x,y) - f(x,y))^2 \right)^{1/2}$$

The *signal to quantization noise ratio* (SQNR) is the ratio of the signal power to the RMS error:

$$\mathrm{SQNR} = 10 \log_{10} \frac{\left(\sum_x \sum_y g(x,y)^2 \right)^{1/2}}{N e_{\mathrm{rms}}}$$

The SQNR is typically computed relative to either the reconstructed raw data (data SQNR) or the reconstructed image (image SQNR). Since the process of constructing the image coherently combines signal and non-coherently combines quantization noise, the image SQNR is typically greater than the data SQNR.

SQNR is the most widely used metric for measuring quantizer performance. However, SQNR is an incomplete measure of signal degradation. For example, in Ref. 2 it is noted that encoding/decoding for one compression technique yielded images with severe distortion in the region of bright spots, which was not reflected in the SQNR degradation. In Ref. 3, it is noted that SAR data compressed with different algorithms with comparable SQNR demonstrate different image quality.

Some researchers have developed metrics that aim to more accurately reflect image degradation due to quantization. In Ref. 4, the authors claim the coherence coefficient is a better measure of phase quality, which is a relevant measure of interferometry quality. Benz, Strodl, and Moreira[5] isolate the digitization noise from other system noise. They define a signal-to-digitization-noise-ratio (SDNR) by factoring out the system noise power. McLeod, Cumming, and Seymour[6] show that an estimate of the phase-noise levels of the original interferograms may be made by measuring the coherence magnitude of the data (a measure of the correlation between pairs of images used to create the interferogram), demonstrating that the digitization phase noise is inversely related to the interferogram coherence magnitude level. They provide a thorough examination of the degradation of interferogram digital elevation model accuracy due to quantization noise.

4. SAR COMPRESSION TECHNIQUES

4.1 Block Adaptive Quantization

The first use of onboard compression of raw SAR data was on the Magellan mission to Venus, which utilized block adaptive quantization (BAQ).[1] An (m,n)-BAQ algorithm maps each m-bit symbol to an n-bit symbol. It relies on the fact that although the variations in signal level over a long block can be large, the variations for smaller blocks are limited. The variance of a small block (on the order of 64 to 128 samples) is estimated, and an optimal quantizer for that variance is used on that block. The estimated variance is transmitted with the compressed block, allowing reproduction with a small overhead. The block-floating-point-quantization (BFPQ) algorithm is an extension and generalization of the BAQ algorithm. For the purpose of comparison with other algorithms, we will refer to both as BAQ.

In addition to the Magellan mission, BAQ has been used on SIR-C,[7] SRTM, GeoSAR, ENVISAT,[8] as well as to compress SAR data from Cassini. In most of these cases $(8,4)$-BAQ was used.

4.2 Transform Coding

Transform coding is based on the decomposition of a signal into a set of basis functions. The coefficients of the expansion of each signal are quantized and transmitted. This has allowed large compression ratios for images, and forms the basis for the JPEG2000 standard. The performance achieved in Ref. 3 measured by the raw-data SQNR was little better than for BAQ, although it is noted that the SQNR was not representative of the quality of the final image, which improved with JPEG2000 relative to BAQ. Much better SQNR was demonstrated in Ref. 4 using a transform code with a threshold quantizer.

4.3 Vector Quantization

A vector quantizer (VQ) encodes samples in blocks, mapping them to codewords in a pre-determined codebook. An optimum quantizer would utilize the joint distribution of the symbols in a block. In cases where the joint distribution is unavailable the codebook is formed from a training sequence. Block-gain-adaptive VQ (BGAVQ), described in Ref. 9, extends the approach of the scalar BAQ algorithm to a vector, normalizing each block of data to have (approximately) unit variance, and performing VQ on the scaled block. It has the advantage of requiring a single codebook. The block-adaptive-vector-quantizer (BAVQ), described in Ref. 5, compresses the outputs of the BAQ with VQ.

4.4 Trellis-Coded Quantization and Variants

One can think of trellis-coded quantization as a special case of VQ where the codewords are constrained to be paths on a trellis. The minimum distortion codeword may be chosen by the Viterbi algorithm, allowing quantization of very long sequences with relatively low complexity. Trellis-coded quantization may be combined with VQ by allowing trellis edges to map to a set of codewords. Variations of trellis-coded quantization have been applied to SAR data.[10]

4.5 Entropy-Constrained BAQ

In entropy-constrained BAQ (ECBAQ), the quantizer is followed by an entropy coder. Ref. 11 contains an example of ECBAQ applied to SAR data.

5. PROCESSING AND PARTIAL PROCESSING PRIOR TO COMPRESSION

The conversion of raw SAR data into SAR imagery requires a 2-D matched filter operation, which may be decomposed into a pair of 1-D convolutions: a range-focusing convolution followed by an azimuth-focusing convolution. The convolutions are commonly implemented in the transform domain. The range-focusing operation is relatively straightforward and so it is quite reasonable to propose performing this operation onboard a spacecraft. The azimuth-focusing convolution is much more complicated. Both of these operations have a tendency to make the structure in the data more apparent, suggesting that performing one or both of these steps onboard a spacecraft prior to compression can produce appreciable data compression improvements. A number of researchers have investigated this approach.

5.1 Compression following range-focusing

Compression following range-focusing has been considered in Refs. 12 and 2. Parkes and Clifton[2] applied VQ after several intermediate steps in forming the range-compression convolution: after the FFT on the data, after taking the product of the FFTs, and after the inverse FFT, with both real and complex data in both the range and azimuth directions. The VQ utilized codebooks of 256 vectors, mapping to varying number of symbols in order to vary the compression ratio. Codebooks were formed using training sequences from the data set. They achieved the greatest SQNR by compressing real range samples after the FFT, achieving an SQNR, measured relative to the reconstructed signal, of 9.97 dB at 2 bits/sample. BAQ applied to the same data set returned an SQNR of 8.4 dB at 2 bits/sample.

D'Elia, Poggi, and Verdoliva[12] compared VQ, trellis-coded quantization, and trellis-coded VQ (TCVQ) following range-focusing. In comparisons, they normalize the power of the reconstructed image, so as not to bias the SQNR measure, which is not always explicitly addressed in other papers, and explicitly show measured

SQNR for reconstruction of the raw data and the final image. They show gains with TCVQ over BAQ of 1.8 dB at 1 bit/sample and 0.8 dB at 2 bits/sample. These results were obtained with an 8-state trellis, codebooks containing 256 code-vectors, and sample vectors of length 8 (1 bit/sample) and 4 (2 bits/sample). They address issues of complexity, and provide a number of lower-complexity TCVQ options.

5.2 Frequency Filtering

Further gains are possible by using different levels of quantization on coefficients in the frequency domain (up to possibly discarding some coefficients). Benz, Strodl and Moreira[5] propose performing a 2-D FFT on the data, then perform different levels of quantization on the coefficients, according to the energy in the different frequency bands. They discard data outside the signal bandwidth, achieving a reduction without significant degradation in signal quality. They illustrate an SDNR of 15.4 dB at 2 bits/sample on an ERS-1 data set, compared to an SDNR of 10.6 dB achieved by the BAQ. Algra[11] performs an FFT on the raw data and filters out, or discards, part of the subsequent spectra. They show that 10% of the spectrum can be discarded in range and up to 30% of the spectrum can be discarded in azimuth. They consider concatenating azimuth FFT filtering with ECBAQ compression. The block-adaptive-bit-rate-control (BABC) algorithm utilizes a varying compression ratio depending on the block variance. The FFT-BABC applies the BABC to the data in the spectral domain[13] resulting in improved performance compared to BAQ.

5.3 Compression following image formation

Very significant improvements in compression performance are possible if the image is formed prior to compression, and furthermore conventional image compression techniques can be used in this case. This approach has been considered by Parkes and Clifton,[2] and by Witzgall and Goldstein.[14] It is important to note that for interferometric applications, a high-quality phase image must be preserved in addition to the amplitude image; this consideration reduces the potential improvement for such applications.

6. HARDWARE DEMONSTRATIONS

In Ref. 15 an onboard SAR processor that incorporates compression of processed SAR images is reported. Processing is accomplished with a single custom chip, designed to satisfy power and size constraints of an unmanned aerial vehicle (UAV). Compression based on the discrete cosine transform (DCT) is applied to the processed images. Further data rate reductions are suggested by utilizing region-of-interest filtering.

The *Technology Development of a Spaceborne On-Board SAR Processor and Storage Demonstrator* (TOPAS) project was conducted by the German Space Agency from 1999-2002.[13,16] The goal was to demonstrate onboard processing and compression of SAR data. Three methods were considered for data rate reduction. The first was varying the sampling rate as a function of the incidence angle to yield a constant, or maximum, ground range resolution. This is accomplished by downsampling prior to any other conversion and is considered lossless. Second, compression of raw SAR data was considered. Finally, processing the data to form images which are then compressed with an efficient compression algorithm was considered.

7. COMPARISON OF RESULTS

In Table 1 we present a comparison of several results from the literature for compression of raw SAR data.

8. CONCLUSIONS

A wide range of compression algorithms have been applied to raw SAR data. The most promising of these are trellis-coded quantization[10] and wavelet-based compression,[4] providing gains of up to 2 dB over the baseline BAQ compression. However, due to the uncorrelated nature of the raw data, the gains due to compression of raw data are limited. This suggests partially processing the data onboard. Compression following the relative low-complexity step of range-compression has illustrated only modest gains over compression of raw data.[2,12] Larger gains have been observed by transforming the data and applying selective filtering.[5,11,13] If image formation onboard is feasible, very large gains are possible using well known image compression techniques.[2,14]

Table 1. Comparison of SQNR (dB) for various coders of raw SAR data.

Class	Ref	Data	Source bits/sample	Compressed Rate (bits/sample) 1.00	1.25	1.50	1.75	1.80	2.00
BAQ	[10]	Gaussian							8.70
	[9]	"Samothrace"	8						8.9
	[2]	ERS-1	5						9.29
	[5]	ERS-1	5						*10.6*[a]
Wavelet	[3]	SIR-C/X-SAR	6						8.38
	[3]	SIR-C/X-SAR	6						8.70
	[4]	ERS-1	5	5.34[c]		8.8[c]		10.7[c]	11.82[c]
ECBAQ	[11]	ERS	8[b]						9.67
VQ	[10]	Gaussian		4.40	5.99	6.93	8.85		9.30
	[2]	ERS -1	5						9.37
	[9]	ERS-1	5			7.1		8.7	9.8
	[9]	"Samothrace"	8			7.2		8.6	9.7
	[11]	ERS-1	8[b]						10.42
VQ variants	[5]	ERS-1	5						*12.0*[a]
	[9]	ERS-1	5			7.7		9.3	10.4
	[9]	"Samothrace"	8			7.5		8.9	10.0
Trellis Coded Quantiz.	[11]	ERS-1	8[b]						10.74
	[10]	Gaussian		5.19	6.61	7.92	9.57		10.69
	[10]	Gaussian		5.22	6.68	8.20	9.76		11.30
bound	[11]	Gaussian							12.04

Class	Ref	Data	Source bits/sample	Compressed Rate (bits/sample) 2.25	2.50	2.75	3.00	3.50	4.00
BAQ	[10]	Gaussian					14.0		
	[9]	"Samothrace"							
	[2]	ERS-1	5						
	[5]	ERS-1	5						
Wavelet	[3]	SIR-C/X-SAR	6				14.18		
	[3]	SIR-C/X-SAR	6				13.78		
	[4]	ERS-1	5	13.2[c]					
ECBAQ	[11]	ERS	8[b]		13.25		16.17	19.37	22.23
VQ	[10]	Gaussian		11.98	12.45	14.98	14.62		
	[2]	ERS -1	5						
	[9]	ERS-1	5						
	[9]	"Samothrace"	8						
	[11]	ERS-1	8[b]		13.48		16.48	19.48	22.48
VQ variants	[5]	ERS-1	5						
	[9]	ERS-1	5						
	[9]	"Samothrace"	8						
Trellis Coded Quantiz.	[11]	ERS-1	8[b]		13.48		16.48	19.48	22.48
	[10]	Gaussian		12.90	13.56		16.29		
	[10]	Gaussian		12.81	14.36	15.83	17.37		
bound	[11]	Gaussian			15.05		18.06	21.07	24.08

[a] SDNR relative to image
[b] 8 bit samples constructed from 5 bit source
[c] interpolated

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