ADAPTIVE VECTOR QUANTIZATION FOR RAW SAR DATA

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ABSTRACT

This paper proposes an adaptive vector quantization scheme designed for spaceborne raw SAR data compression. This approach is based on the fact that spaceborne raw data are Gaussian distributed, independent, and quite stationary over an interval (in both azimuth and range) which depends on SAR system parameters. The Block Gain Adaptive Vector Quantization (BGAVQ) is a generalization of the Block Adaptive Quantization (BAQ) algorithm to vectors. It operates as a set of optimum vector quantizers (designed by the LBG algorithm) with different gain settings. The adaptation is particularly efficient since, for a fixed compression ratio, the same codebook is used for any spaceborne SAR data. Results on simulated and real images, for data rate of 1.5 to 2 bit/sample, have confirmed the expected performance of the BGAVQ algorithm.

INTRODUCTION

This paper deals with strip mapping mode SAR. The SAR signal data, usually called raw data, is supposed to be collected from a high resolution spaceborne SAR.

Synthetic Aperture Radar (SAR) is a well known method for improving the resolution of radar imaging systems without increasing the physical antenna size [1,2]. The high resolution is achieved by processing a sequence of radar returns from a moving transmitter to simulate a very long antenna array. The net effect is that the SAR system is capable of achieving a resolution independent of the sensor altitude.

However, image generation requires substantial computation. Therefore, given the current technology, raw data on-board storage and downlink transmission will be considered. The high data rate of future SAR systems is often incompatible with the available communication channels or recorder storage. Thus, a reduction of raw data rate is necessary.

To preserve the system design, data compression techniques can be employed. Until now, a technique called Block Adaptive Quantization (BAQ), and a similar one referred to as Block Floating Point Quantization (BFPQ), have been selected for on-board raw data compression [2,3]. Nevertheless, other data compression techniques have been considered [4,5,6]. Several studies conclude that Vector Quantization (VQ) of raw data exhibits good performance [5,6,7].

This paper proposes a new approach for spaceborne raw SAR data compression; it consists in a vector quantizer which adapts to the changing level of the signal. Section I presents the SAR data features which are the basis for the BAQ design given in section II. Section III briefly describes the VQ. The proposed raw data compression technique is explained in section IV. With this adaptive VQ, we will establish that only one optimum codebook is used for any raw data. Results achieved on two different data sets are presented in section V.

I. RAW DATA FEATURES

According to signal processing, the backscattered signal is viewed as a (complex) random variable whose real and imaginary parts show particular statistics. We propose here a brief reminder; for more details, we suggest the reader to refer to [2,3].

Each radar pulse illuminates a delimited surface area which consists of many scattering points. The echo s_k of a scatter is viewed as a complex number:

$$s_k = a_k e^{j\phi_k}$$

where a_k represents the amplitude and ϕ_k the phase related to the path distance. It is obvious that a_k and ϕ_k are independent. Since range varies rapidly from scatter to scatter with respect to the wavelength of the transmitted signal, we can assume that the phases ϕ_k are uniformly distributed between $[-\pi , \pi]$, and are independent.

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The radar return from the scatters is the coherent addition of the elementary echoes $S = \sum s_k$. Thus, real and imaginary parts have zero means, identical variances, and are uncorrelated. Considering the very large area encompassed by the radar footprint, the "central-limit" theorem can be invoked to assume that their probability density functions are Gaussian. These assumptions involve that magnitude has a Rayleigh density and phase is uniformly distributed. This means that successive samples, in both range and azimuth directions, are uncorrelated. However, the variation in power of the return is a slow function of range, due to the pulse compression technique (chirp), and azimuth, because of the system geometry: the surface area encompassed by the antenna beam is nearly the same from pulse to pulse.

These statistics are the basis for the BAQ design.

II. BLOCK ADAPTIVE QUANTIZATION

Fundamentally, the BAQ algorithm consists of an optimal Scalar Quantizer (SQ) which adapts to the changing level of the input signal. An optimal quantizer is controlled by the statistics of the source [8]. Since real and imaginary parts of raw data are Gaussian with zero means, the distribution $f(x)$ can be completely specified with the standard deviation σ.

The slowly varying echo power in range and from pulse to pulse guarantees that over a given interval, i.e. a block of data, the statistics are quite similar. Thus, the BAQ algorithm divides the digitized raw data into blocks and evaluates the σ within each block in order to determine the optimum quantizer.

A single value (σ) is transmitted for each data block; therefore, the compression ratio is essentially determined by the SQ used to encode blocks. In the case of the Magellan spacecraft mapping Venus, a 2 bit quantizer was adopted for real and imaginary parts.

Note that the BFPQ algorithm consists in the same adaptive technique. The difference with the BAQ algorithm is that it uses an uniform scalar quantizer.

III. VECTOR QUANTIZATION

VQ is a generalization of the scalar quantization to vectors (groups of pixels); it is capable of providing great performance on a wide variety of sources, including images [9] and SAR [5,6,7]. It takes advantages of [10]:

- the space filling properties,
- the probability density function shape of the source,
- both linear and non linear dependencies between vector components.

VQ is a mapping of an input vector X, onto a representative vector $\hat{X}$ (codevector) in a set of standard vectors (codebook) according to a distortion criterion, commonly the mean square error. The index identifying the best match is transmitted to the receiver which has an identical codebook. Therefore, the quantized vector, $\hat{X}$, is reconstructed from the index by a table look up operation.

The most important step for VQ is the codebook design. Y. Linde, A. Buzo et R.M. Gray (LBG) expands the algorithm developed by Max-Lloyd to form an optimum design for VQ [11]. Because the joint probability is generally unknown, the LBG algorithm uses a large training set statistically representative of the expected source to find the “codevectors”. The codebook is then constructed by minimizing a distortion criterion on vectors of the set.

Since the data rate depends only on the number of codevectors and on their dimension, VQ allows to achieve low rates (or intermediary rates) in comparison with SQ.

IV. BLOCK GAIN ADAPTIVE VECTOR QUANTIZATION

In section I, we established that the raw data statistic is Gaussian with zero mean. We also showed that these data are uncorrelated. From these two statements, we can assume that the real and imaginary parts are independent Gaussian random variables. This is the basis of the proposed technique.

Since raw data are independent, the joint probability satisfies:

$$f(x_1, x_2, \cdots, x_n) = f(x_1) f(x_2) \cdots f(x_n)$$

Thus $f(x_1, x_2, \cdots, x_n)$ is Gaussian with zero mean. As in the 1D case, it is completely specified by the standard deviation σ. This remark is very important for VQ. It means that a unique codebook exists to encode any raw data with equal σ.

The slowly varying echo power of the raw data in range and azimuth, allows the block estimation of the σ. If the gain (σ) of each block is equalized, the whole blocks of the raw data will have the same statistics. Therefore, a unique codebook, designed from a set of Gaussian data with zero means and unit variances, is used for real and imaginary parts of any raw data.

The Block Gain Adaptive Vector Quantization (BGAVQ) is a generalization of the BAQ algorithm to vectors. In fact, this algorithm operates as a set of optimum vector quantizers with different gain settings. Note that this technique is different from the Gain Shape VQ [8] in the sense that the adaptation operates on blocks of vectors, and not on vectors.

The following figure shows a block diagram of the BGAVQ algorithm, used for real and imaginary parts.

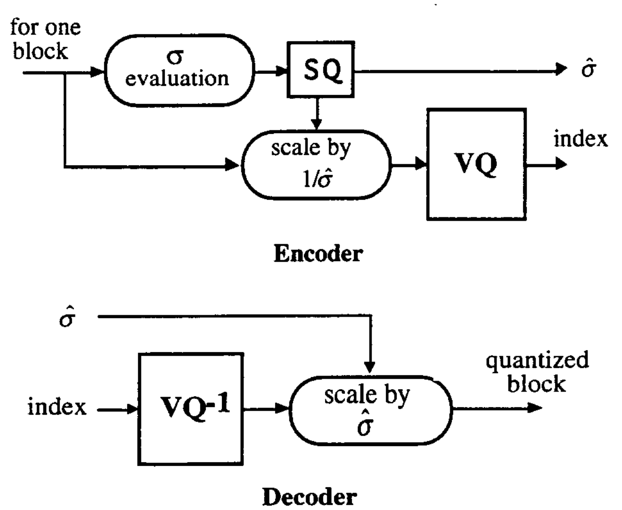

Figure 1: Block diagram of the Block Gain Adaptive Vector Quantization (BGAVQ).

- For each input data block, the standard deviation σ is estimated, quantized and transmitted.

- Each sample in the block is scaled by the corresponding $\hat{\sigma}$.

- The result is vector quantized.

- The decoding process starts with the VQ^{-1}; the final quantized data is achieved by scaling the samples by the corresponding gain of the block.

Note that an equivalent way to do is to scale all codevectors of the codebook instead of scaling each input vector. This scheme may be simpler if the codebook size is smaller than block size.

V. EXPERIMENTAL RESULTS

The BGAVQ was applied on two data sets. One, called "simu2", was simulated using "Samothrace" (a simulator designed by AEROSPATIALE [12]). Real and imaginary parts are digitized on 8 bits per sample; their entropy is about 6.5 bits. The second one, acquired by the ERS-1 satellite, represents the scene of "Cazaux" (France). This real data set is sampled at 5 bits for each Cartesian component; the entropy is around 4.7 bits. Note that these two data sets are completely different. "Simu2" is supposed to be collected from a 30 km altitude sensor, which has a range and azimuth bandwidth time product of 400 and 63 respectively. Its size is relatively small compared to the scene "Cazaux" which was collected at 800 km altitude, and presents a range / azimuth bandwidth time product about 500 and 1000 respectively.

These factors are very important for the selection of the block size. The blocks should contain a sufficient number of samples to establish Gaussian statistic, but also be small enough relative to the variation in power. According to [2], the data is approximately stationary over 1/4 of the pulse and synthetic aperture lengths. We chose to split "simu2" into 64×16 blocks, and "Cazaux" into 64×128 blocks.

BGAVQ is compared in terms of Signal to Noise Ratio (energy ratio) with VQLBG at different rates (fig. 2 and 3). The rate is given for each Cartesian component.

In the case of "simu2", we present the results obtained on real and imaginary parts of raw data (before processing) and on reconstructed images (the magnitude after processing). The SNR achieved by the BAQ is given for reference. Note that results on real and imaginary parts are similar since their statistics are identical.

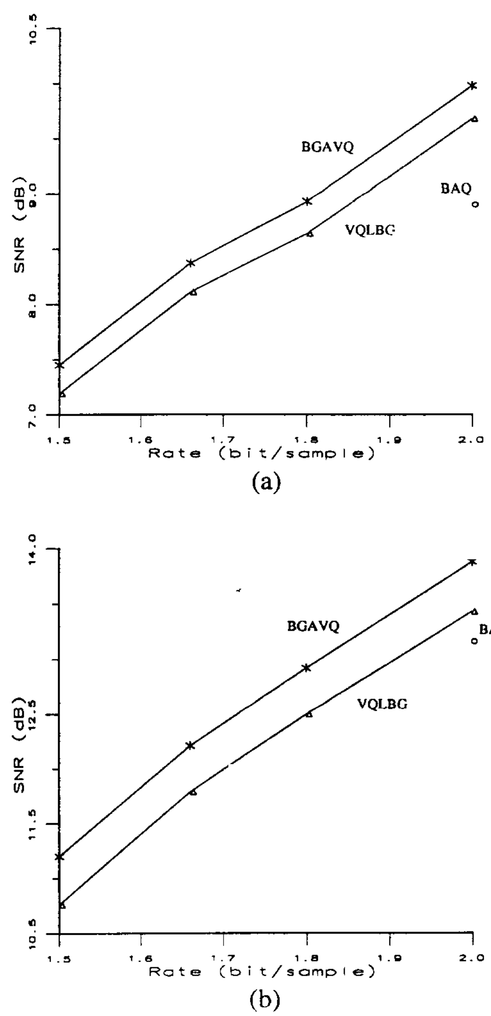

Figure 2: SNR versus rate: "simu2"
(a) before processing, (b) after processing.

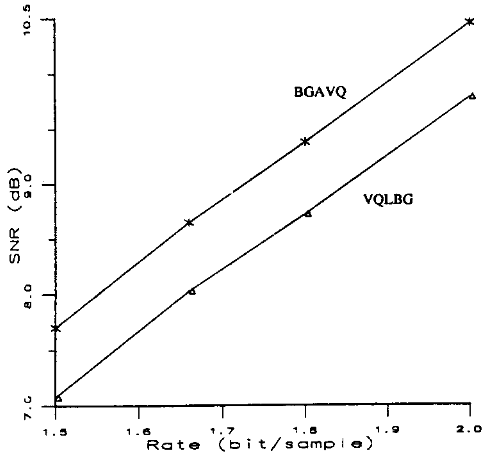

Figure 3: SNR versus rate: "Cazaux" (before processing).

The codebooks, used by the VQLBG algorithm, have to be designed from the data to be encoded. On the contrary, for a fixed compression ratio, the BGAVQ technique always uses the same "Gaussian codebook".

In comparison with VQLBG, we achieved better performance on "Cazaux" scene because the variation in power (in relation with its size) is more important than "simu2" scene.

Note that image VQ produces edges which look like staircases, especially when high compression ratio is required. In the case of raw SAR data, this "blocking effect" is not a problem because the quantized raw data are followed by the SAR focusing algorithm [5].

VI. CONCLUSION

An adaptive vector quantization scheme for raw SAR data has been presented. This approach is based on the fact that spaceborne raw data are Gaussian distributed, independent, and quite stationary over an interval which depends on SAR system parameters. For a fixed compression ratio, this adaptive vector quantizer always uses the same codebook, with particular features. Therefore, no on-board hardware is required for its generation. Results on simulated and real images have confirmed the expected performance of the BGAVQ algorithm.

For spaceborne processing consideration, we are now investigating the reduction of the encoding complexity, in particular by using Lattice Vector Quantizers.

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