Nationaal Lucht- en Ruimtevaartlaboratorium
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ABSTRACT

For the compression of raw SAR (Synthetic Aperture Radar) data on-board spacecraft, the Block Adaptive Quantization (BAQ) algorithm is often used due to its effectiveness and low implementation complexity. However, the Entropy-Constrained Block Adaptive Quantization (ECBAQ) algorithm outperforms BAQ with respect to Signal-to-Quantization-Noise-Ratio and equals the performance of more complicated methods such as Vector Quantization and Trellis Coding variants.
ECBAQ can be implemented using an architecture that is essentially not more complicated than that of a BAQ encoder and suitable for high-speed implementations. Moreover, the method features bit rate programmability with non-integer rates. This allows the SAR information throughput to be optimized for different types of applications.

INTRODUCTION

Compression of raw SAR data has been applied for the first time in the NASA Magellan mission to Venus (1989-1994). The ASAR data from ENVISAT will also be transmitted in a raw compressed format. The type of compression applied in these cases is called *Block Adaptive Quantization* .
In most SAR systems the echo signal received is down converted and split into I and Q components. These components are then digitised separately by two A/D converters. The radar returns can be viewed as a superposition of the responses of many small scatterers [1], with elementary phasors that are characterised by the following properties:

a) The reflectance amplitudes and the phase delays are statistically independent of each other and of all other amplitudes and phases
b) The phases are uniformly distributed because the scatterer range is unknown and the SAR resolution is much greater than the radar wavelength

Hence the real and imaginary parts of the complex signal have zero means and identical variance, and are uncorrelated. The real and imaginary parts of the complex signal are sums of extremely large numbers of independent random variables due to the relatively large footprint area. From the central limit theorem it follows that the real and imaginary parts are asymptotically Gaussian with the same variance. The variance of the samples only slowly changes between successive blocks of samples.
Up to now, the Block Adaptive Quantizer (BAQ) has been selected for on-board data compression in space [1], [2]. First, the raw SAR data is divided into rather small-size blocks, not necessarily squared. Let these data be represented in b bits/sample, I and Q values. For each block the standard deviation is calculated. Second the data is quantified. Assume Q is a quantizer with quantization cells and output levels $\left\{R_i, y_i; i = 1, \cdots, N = 2^R\right\}$ where R is the resolution of the quantizer. Q is designed to minimise the Mean Squared Error (MSE). This leads to a quantizer known as the Lloyd quantizer, with non-uniform decision regions. The thresholds of Q for a Gaussian memoryless source are well known and tabelized. The resulting compression ratio is b/R.

THE ENTROPY-CONSTRAINED BAQ

The scalar quantizer designs used for the Block Adaptive Quantizers described in [1] and [3], are Lloyd quantizers. Given the number of reproduction values, i.e. the codebook size, the design process iterates to optimal threshold values such that the total sum of the mean squared error is minimised.
The output of the quantizer is a discrete alphabet source that can be followed by an entropy coder. A reasonable question is: if a quantizer is followed by an entropy code, then should the quantizer be designed as previously described? Or: has the use of a quantizer in cascade with an entropy coder an effect on the design philosophy?
Hence, the design objective is to achieve the minimal mean squared error for a certain, <u>constrained</u> output entropy (rather than a fixed codebook size). Ref. [4] describes the theory behind this problem. It can be shown that (surprisingly):

1. the optimum quantizer is the uniform quantizer and <u>not</u> the Lloyd quantizer
2. the approximate average distortion achievable by uniform quantization and entropy coding can be compared with the Shannon optimum performance as given by the distortion-rate bound. In particular, if the source is memoryless (like raw SAR data), the average rate is only 0.255 bits from the Shannon optimum. Note that this is bit rate independent.

Ref. [5] shows that this remains true for a variety of memoryless sources even for low bit rates.
One could state that the drawback of such a scheme is the use of an entropy coder with its resulting variable bit rate and the complexity involved. However, it will be shown that complexity does not have to be an issue in this particular case. A finite-state machine (FSM) based Huffman algorithm perfectly matches the type of alphabet sources we have to encode.
Secondly, often, on-board SAR data is not immediately transmitted to the ground but temporarily stored in a mass data memory. But, if even not, slight variations in coder output bit rate can be easily controlled by the use of a data buffer memory.
The design process of such a quantizer is rather straightforward. We can formalise this process by the following algorithm:

Step 0: Initialisation
Given: A memoryless IID Gaussian source with standard deviation σ, a target output entropy of *R* bits/symbol, an initial number of quantizer output values $C = int(2^R)$, a value ε
Step 1:
Let the stepsize $S_C = 2 * A_{\max} / C$
Step 2:
Calculate the output entropy *H(C,S)* of the quantized symbols and the associated mean squared error *N(C,S).*
Step 3:
If $H(C,S) > R$ then $S_C := S_C - 1$ and goto Step 2
Step 4:
If $N(C,S_C) - N(C-1,S_{C-1}) > \varepsilon$ then $C := C+1$ and go to Step 1 ; otherwise stop.

SIMULATION RESULTS

This section presents simulation results with a Gaussian Independently and Identically Distributed (IID) source, represented in 8-bit values and a standard deviation parameter σ varying between 0 and 0.5 of the maximum amplitude $A_{max} = 127$.
The results confirm that Entropy-Constrained Scalar Quantization outperforms the Lloyd scalar quantizer. The results of the ECSQ design for a Gaussian IID source with σ=0.25, are presented in Fig. 1, where the Signal to Quantization Noise Ratio is given as a function of the quantizer output entropy. From the graph it can be concluded that indeed the difference with the Shannon bound approaches the theoretical 0.255 bits, and that every non-integer rate can be approximated by a number of (C,S)

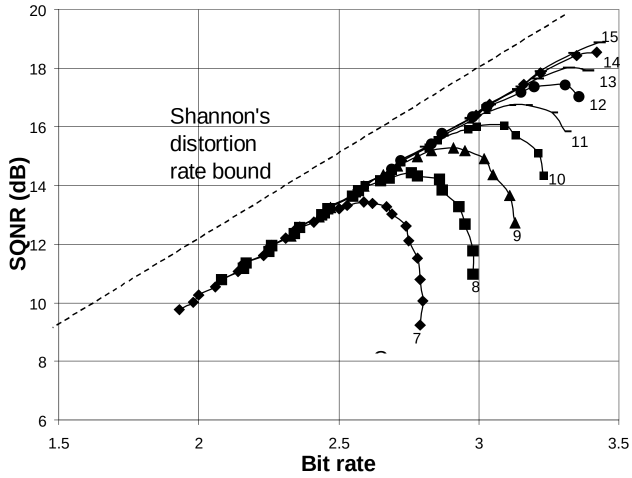

Fig. 1 SNQR of ECSQ as a function of the output entropy for a Gaussian IID source σ with =0.25

output combinations. Obviously, for every coding rate R and standard deviation σ, an optimal (C,S) combination exists resulting in maximal SNR.
ECSQ can be extended to an Entropy-Contrained Block Adaptive Quantizer (ECBAQ) by adding on-the-fly σ calculation and correspondingly adapting the quantizer function and the entropy coder on a block-by-block basis. Table 1 compares the results of ECBAQ with conventional BAQ and more complex methods such as 4-dimensional vector quantizing and Trellis Code Quantization [8].
The gain of ECBAQ over BAQ is 1.5 dB to 2 dB in the range from 3 to 4 bit/sample. Another interesting feature compared to the Lloyds quantizer is the response on a deviation of σ. If the σ of the input signal differs from the σ value for which the quantizer-coder design has been optimized, then the SQNR and the rate will change (Fig. 2). But the overall performance will not deteriorate in the sense that the system does not drift away from the Shannon bound. This property can be exploited in a practical design.

IMPLEMENTATION ISSUES

Although ECBAQ includes an entropy coder, for example a Huffman scheme, the design is essentially not of a higher complexity than that of a conventional BAQ. A Huffman coder can be implemented as a finite-state machine [6]. Ref. [7] shows how this concept can be realized using a fast Look-Up Table (LUT) method and that it can be constructed in such a way that it generates complete bytes (8 bits) or words (16 bits) only.
This leads to the architecture of Fig. 3 where the LUT is stored in two cascaded Random Access Memories

(RAM). The first one comprises the adaptive quantizer. The input samples (8 bits), the current σ (4 bits), and the programmed rate (4 bits), are combined into one 16-bit

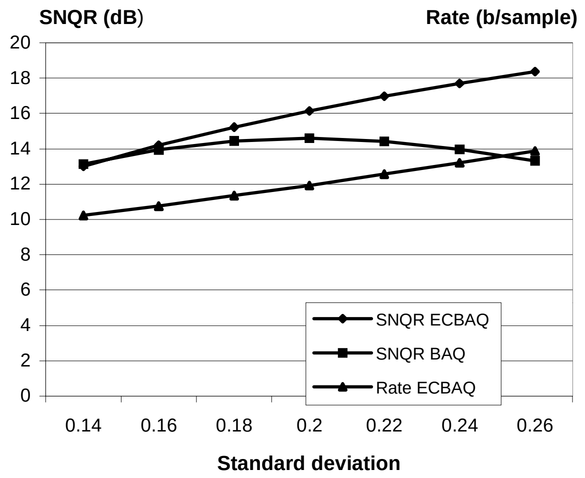

Fig. 2 SNRQ of ECBAQ and BAQ both optimised for σ = 0.2, 3 b/s, as function of the signal's standard deviation

Table 1 SNRQ in dB of ECBAQ compared with the Shannon bound R(D), BAQ, 4-dimensional Vector Quantization, and Trellis Coded Quantization

rate b/s	R(D)	BAQ	VQ4	TCQ2	ECBAQ
2	12.04	9.3	10.42	10.74	9.67
2.5	15.05		13.48	13.56	13.25
3	18.06	14.63	16.48	16.56	16.17
3.5	21.07		19.48	19.56	19.37
4	24.08	20.24	22.48	22.56	22.23

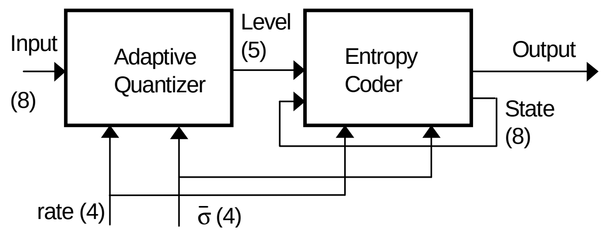

Fig. 3 Architecture of a fast ECBAQ encoder

address pointing to the index of the quantizer output level (5 bits). The second RAM contains all the applicable Huffman codes in FSM form. The RAM is addressed by a combination of the previous state of the FSM (8 bits), the current σ, and the programmed rate. The output consists of the next state (8 bits), an indicator for the number of output code bytes (0, 1, or 2), and, if applicable, the output code bytes themselves. The size of the first RAM should be at least 64 kBytes, apart from parity codes. The size of the second RAM is 8 Mbytes, but can be reduced by the application of truncated Huffman coding and/or less programmable rates. The state is fed back using a latch circuit. The standard deviation σ is calculated on blocks of 64 or 128 samples like in BAQ coding. Note that the throughput of the coder is only limited by the speed of the RAMs. An interesting option is to use the linear dependence of coding rate and SNQR of the signal power as depicted in Fig. 2. By adjusting "σ" (slightly lower or higher than the measured source's σ) the rate can be controlled so that output buffer overflow or flush is avoided. This is important for direct-to-ground-link concepts. Note that a carefully designed rate-control loop even may eliminate the need for continuous σ calculation.

CONCLUSIONS

Entropy-Constrained Block Adaptive Quantization is an attractive option compared to BAQ because

- ECBAQ outperforms BAQ with respect to SQNR
- ECBAQ is rate programmable (non-integer rates) and rate controllable

A conceptual architecture of an ECBAQ coder has been presented which is characterised by its principally high-speed throughput, and its easy programmability. This makes the concept suitable for a large range of applications.

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