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Data compression for operational SAR missions using Entropy-Constrained Block Adaptive Quantisation

Theo Algra

National Aerospace Laboratory NLR
 Anthony Fokkerweg 2 1059 CM Amsterdam
 algra@nlr.nl

Abstract- Operational SAR satellite missions impose new requirements to on-board data compression such as a higher data reduction ratio, more flexibility, and faster data throughput. A novel approach is Entropy-Constrained Block Adaptive Quantisation (ECBAQ). This method outperforms currently used Block Adaptive Quantisation with respect to Signal-to-Quantisation-Noise-Ratio and equals the performance of more complicated methods such as Vector Quantisation and Trellis Coding variants. The ECBAQ algorithm 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 optimised for different types of applications. It is suitable for the application of region-of-interest coding and can be cascaded with frequency filtering to achieve even more data reduction.

I. INTRODUCTION

Raw SAR data compression has been applied for the first time in the NASA Magellan mission to Venus from 1989 to 1994 [1]. Also the ASAR data from the ENVISAT satellite is transmitted in a raw compressed format [2]. The type of compression applied in these cases has been called Block Adaptive Quantisation (BAQ). Raw SAR data compression is not lossless. The digitization and coding process introduce additional noise and effects on the SAR images to be processed. An important quality parameter is the Signal to Quantisation Noise Ratio (SQNR). For example, with ENVISAT in practice a compression ratio of 2 will be used, with SQNR of ~ 19-20 dB.

Until today most space SAR sensors have been built to fulfil scientific or technology demonstration objectives. But the coming years will show a trend towards more and more operational use of remote sensing data. This will have its impact on the user and the system requirements imposed on on-board data compression. In Section II we will assess these changes and try to formulate a set of requirements that will cover the needs of on-board compression of SAR data for future missions. In Section III a novel algorithm for SAR compression is presented, that is able to meet these requirements: Entropy-Constrained Block Adaptive Quantisation (ECBAQ). Section IV reports on simulation results with ECBAQ including experiments to further reduce the complexity of the implementation, while the combination of ECBAQ with frequency filtering is discussed in Section V. Section VI discusses hardware realizations, followed by a number of conclusions in Section VII.

II. REQUIREMENTS

Obviously, one of the driving factors in operational remote sensing is the cost per bit. Large scale use of data will only boost up if the data becomes affordable. An important element of this cost is the data generation capacity of the satellite/sensor system. Developments today show that space SAR systems are evolving to higher spatial resolutions due to advancing instrument technology and consequently higher payload data rates. However, the amount of data that can be downloaded during the pass over the ground station is more and more a serious bottleneck. Without data reduction methods, only a part of the payload capacity can be exploited unless multiple groundstations are used in a direct read out approach. In other words the imaging capacity of the end-to-end system consisting of satellite and ground station, can be improved significantly by on-board data reduction. Therefore on-board SAR data reduction is of vital importance to operational SAR remote sensing.

Another observation in relation to operationalisation is that in most cases a large and diverse user base has to be served. This implies a broad spectrum of applications and a large range of required quality levels, image co-ordinates, delivery times, and temporal frequencies. In [2], [3], [4] and [5] different required quality levels for various types of applications are described, ranging from visual interpretation to interferometry and DEM generation. Consequently, besides data compression, effective on-board data reduction for operational use may be based on the following key points:

- Only the data from areas for which there exists an explicit imaging request are stored in the Solid State Mass Memory (SSMM) for sub-sequent downloading.
- The quality level of the stored data should be in line with the application for which the request is made. In general, it is not efficient to represent the data with a quality level that is higher than required.
- Region-Of-Interest (ROI) coding is supported. A lot of applications do not require a high level of image quality over the complete requested area, but only at one or more regions within the area. Consequently only those smaller areas are represented at the higher quality level. Compare also the emerging JPEG2000 standard [6].

Therefore, an essential requirement of on-board data compression is rate programmability [3], preferably including non-integer rates. Integer rates (like the BAQ compressor at ENVISAT) limit the number of quality levels in practice to only three with intermediate SQNR steps of 6 dB. Assuming that the required SQNR levels are uniformly distributed, then the average SQNR level is in fact ≈ 3 dB higher than required. In



other words the resulting bit rate is 0.5 bit/sample higher than needed, on the average. Therefore non-integer rate programmability is more efficient.

On-board SAR processing and subsequent image compression potentially may reduce the data stream by one or two orders of magnitude. Essentially, this should include the multi-looking process. Multi-looking is normally used on ground to reduce the speckle noise. However in the on-board SAR processing it is the crucial step to reduce the large amount of data and to achieve considerable compression. Moreover, the resulting speckle noise reduction increases the correlation between the samples and improves the effectiveness of the subsequent on-board image compression. However for a number of applications such as polarimetric classification and interferometry the single look complex image is required. In other words, on-board SAR processing can not be applied in all situations. Therefore efficient on-board raw SAR data compression remains necessary.

This leads to a number of requirements with respect to data compression for the coming generation of SAR satellites.

1) Compression ratio

The current de facto standard of SAR compression, BAQ, achieves an SQNR of 20 dB at a compression ratio of 2. But a higher ratio is preferred and can be obtained by more advanced coding techniques.

2) Rate programmability

The compressor should be adaptable to the currently requested level of quality, preferably by non-integer rates, in order to maximize the mean compression ratio. The rates that can be programmed should range from 1.5 (low quality) to 4 (high quality).

3) ROI coding

Region-Of-Interest coding should be supported. This is in line with the programmability requirement, but adds the need for a capability to change the rate several times instantaneously during the imaging process.

4) Speed

The target data throughput is ≥ 100 MC/s [7].

III. THE ENTROPY-CONSTRAINED BAQ

Currently, the Block Adaptive Quantiser (BAQ) is the common approach to on-board SAR data compression. First, the raw data is divided into rather small-size blocks, not necessarily squared. Let these data be represented in b bits/sample. For each block the standard deviation is calculated. Second the data is quantified. Assume Q a quantiser with quantisation cells and output levels $\{R_i, y_i; i = 1, \dots, N = 2^R\}$ where R is the resolution of the quantiser. Q is designed to minimize the Mean Squared Error (MSE). This leads to a quantiser known as the Lloyd quantiser, with non-uniform decision regions. 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 minimized. Raw SAR data can be modeled as a Gaussian memoryless source with slowly changing variance. The thresholds of Q for a Gaussian source

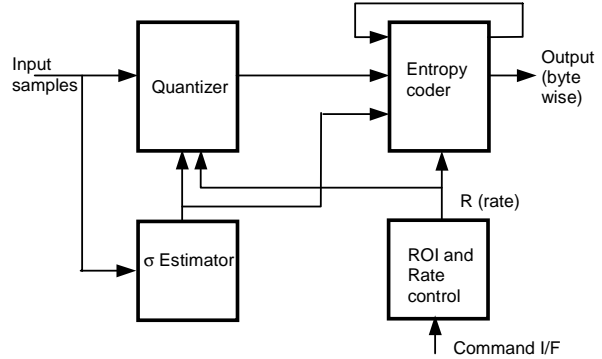


Fig. 1 Functional block diagram of ECBAQ compressor

are well known and tabellised. The resulting compression ratio is b/R . The output of the quantiser is a discrete alphabet source that can be followed by an entropy coder. A reasonable question is if a quantiser is followed by an entropy coder, then should the quantiser be designed as previously described? Or has the use of a quantiser 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, constrained output entropy (rather than a fixed codebook size). In [8] the theory behind this problem is described. It can be shown that

- 1) the optimum quantiser is the uniform quantiser and not the Lloyd quantiser
- 2) the approximate average distortion achievable by uniform quantisation 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 (this is the case with raw SAR data), the average rate is only 0.255 bits from the Shannon optimum. Note that this is bit rate independent.

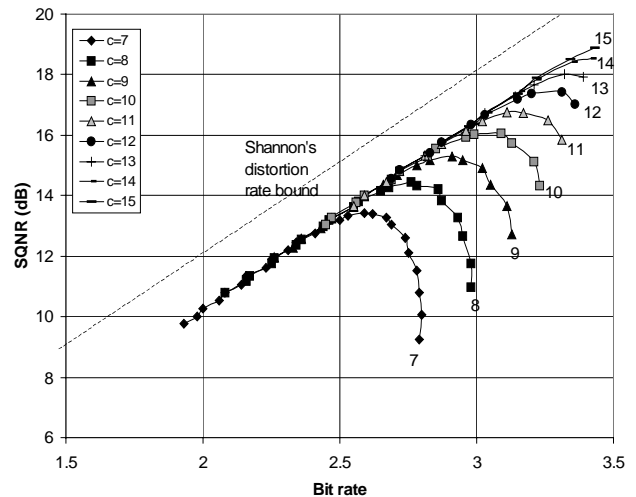


Fig. 2 Signal to Quantisation Noise Ratio as a function of the output rate for a Gaussian source

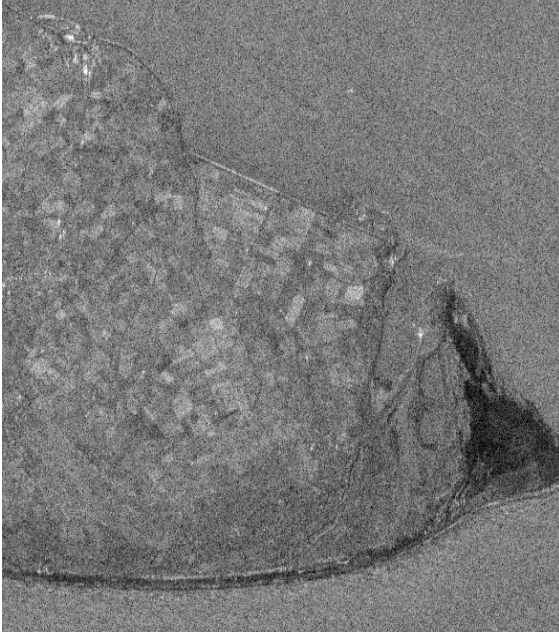


Fig. 3 Southern part of Texel. Part of the slant range SAR image used for the simulations. The image shown is a 4-look image, for better visibility.

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 based 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 quantiser is rather straightforward. We can formalise this process by the following algorithm [9]:

Step 0: Initialisation

Given: A memoryless IID (independently and identically distributed) Gaussian source with standard deviation σ , a target output entropy of R bits/symbol, an initial number of quantiser output values $C = \text{int}(2^R)$, a value

Step 1:

Let the step size $S_C = 2 * A_{\max} / C$ with A_{\max} the maximum amplitude

Step 2:

Calculate the output entropy $H(C, S)$ of the quantised 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 $N(C, S_C) - N(C-1, S_{C-1}) > \epsilon$ then $C := C+1$ and go to Step 1, otherwise stop.

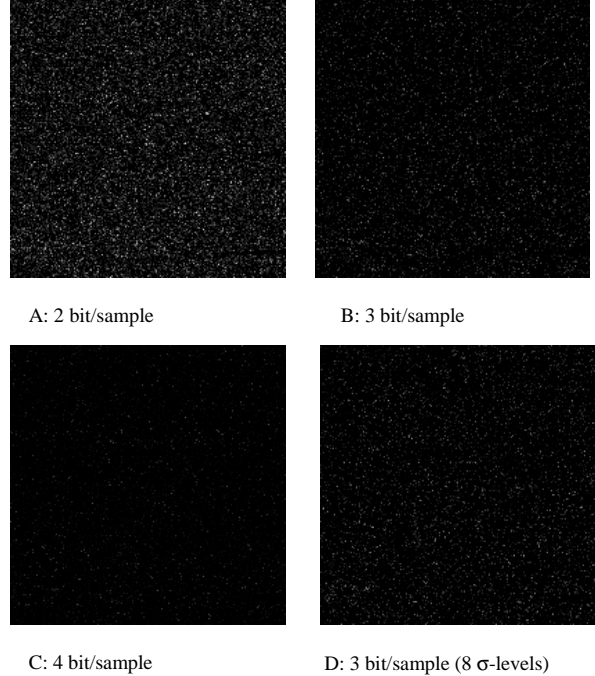


Fig. 4 Parts of the difference images (original single look minus (de)compressed single look)

Fig. 1 shows a functional block diagram of an ECBAQ encoder. The quantiser levels as well as the entropy code depend on the standard deviation of the current block of samples. The block size may range from 16 to 128. Consequently the value of the calculated standard deviation has to be multiplexed into the output bitstream to enable the decoder reconstructing the signal.

IV. SIMULATION RESULTS

Fig. 2 shows the Signal to Quantisation Noise Ratio as a function of the output rate for a stationary Gaussian source as obtained from simulations. From the graph it can be concluded that indeed the difference with the Shannon bound approaches the theoretical 0.255 bits. Two other observations can be made:

- Practically every non-integer output rate can be approximated by a number of (C, S) combinations
- Apparently, the achievable SQNR is equal to $SQNR = 6R - 1.40$ dB

The theoretical bound is $10 \log 2^{2(R-0.225)} = 6R - 1.34$ dB. The difference of 0.06 dB can be explained by the fact that the simulation experiment is based on 8 bits values, which reduces the accuracy of the output values somewhat. Obviously, for every coding rate R and standard deviation σ , an optimal (C, S) combination exists resulting in maximal SQNR.

The Entropy-Constrained Block Adaptive Quantiser (ECBAQ) is constructed by adding on-the-fly calculation and correspondingly adapting the quantiser 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

TABLE I
SQNR OF ECBAQ COMPARED WITH THE SHANNON BOUND R(D), BAQ, 4-DIMENSIONAL VECTOR QUANTISATION, AND TRELIS CODED QUANTISATION (IN DB)

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

such as 4-dimensional Vector Quantisation and Trellis Code Quantisation [10]. The gain of ECBAQ over BAQ is 1.5 dB to 2 dB in the range from 3 to 4 bit/sample.

The data used for the simulation is an ERS file covering the north-western part of the Netherlands. The 5-bits ERS data have been preprocessed into 8-bits raw SAR data, i.e. the data were multiplied by 8 after which a noise component of 3 bits was added. The noise component was shaped in such a way that the resulting data still approximates a Gaussian distribution. Fig. 3 shows a part of the multi-look representation of the slant range image. The raw image contains 4000 lines of 5616 complex samples. Table 2 gives the results of the simulations for the image domain. The results confirm the expected gain in performance of ECBAQ over BAQ (up to 2 dB). When the block size is changed (sizes of 128, 64, 32, 16, respectively) the SQNR changes from 20.74 to 20.71 dB, which is a minor difference. The difference in performance between the use of σ -estimation based on the current block and the previous block is also negligible: 20.72 and 20.69 dB, respectively.

TABLE II
IMAGE DOMAIN RESULTS OF BAQ AND ECBAQ

Rate b/s	SQNR magnitude (dB)	Rms Phase Error	abs. mean Phase Error	wght. rms Phase Error
BAQ				
2	13.68	28.86°	17.39°	13.04°
3	19.22	17.02°	9.23°	6.49°
4	24.83	9.76°	4.84°	3.31°
ECBAQ				
2	14.46	27.11°	16.12°	11.96°
2.5	17.76	19.66°	10.96°	7.8°
3	20.72	14.69°	7.78°	5.42°
3.25	22.29	12.6°	6.5°	4.49°
3.5	23.87	10.74°	5.41°	3.71°
3.75	25.32	9.28°	4.57°	3.12°
4	26.69	8.06°	3.89°	2.65°

Finally simulations have been performed to investigate the results for a decreasing number of σ -levels. This is interesting since it may result in a major reduction of implementation complexity. It can be concluded that with ECBAQ the use of only eight σ -levels is sufficient. This is a major difference with BAQ. The reason for this difference is that a deviation of the input variance from the one for which the current used coder is optimized does not result in a reduction of performance. With ECBAQ the bit rate as well as the SQNR are proportional to the input deviation. But the distance to the Shannon bound does not change as is explained in [9].

Finally fig. 4 presents a number of difference images (original – compressed/decompressed). Only a small part of the covered area is shown to enable observation of the image details. Fig. 4-D shows the difference image in the case of a limited number of σ -levels.

V. FREQUENCY FILTERING

In addition to ECBAQ, the application of frequency filtering potentially increases the compression ratio [3]. The principle is to perform a Fast Fourier Transform (FFT) on raw data blocks, in order to transmit to the ground only the useful part of the data spectra. Hence it is possible to remove on-board the cut-off part of the spectrum and substitute it on ground with zeroes. In range direction typically at least 10% of the spectrum can be removed. Along the azimuth even 30% can be reached. The implication is that the Doppler centroid has to be known on-board. Basically, the ECBAQ can be preceded by one (azimuth) or two (azimuth and range) FFT frequency filtering blocks [11]. The FFT size should be equal to the ECBAQ block size. Although in azimuth direction there is some flexibility due to the fact that the ECBAQ only operates on blocks of one azimuth line wide. In azimuth direction a buffer is needed to store N range lines, where N is the FFT size. For example a SAR compressor can be composed of an azimuth FFT block followed by an ECBAQ. This will result in an overall compression ratio of ~ 8:2.6 to 8:1.3. Refer to figure 5. Hence frequency filtering is an attractive option to increase the data compression ratio of raw SAR data.

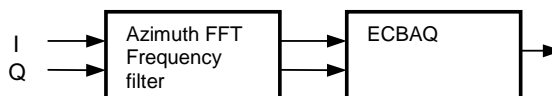


Fig. 5 Functional Block Diagram of SAR data compressor with frequency filtering

VI. IMPLEMENTATION ISSUES

The ECBAQ encoder consists of three main elements: the programmable quantiser, the sigma estimator, and the programmable entropy coder. The quantiser's step size and number of thresholds depend on the programmed output rate and the standard deviation of the current block of input samples. The entropy coder includes a code tree mechanism for every possible combination of output rate and standard deviation. The sigma estimator calculates the standard deviation of the current block of samples (fig. 1). Both the quantiser and the entropy coder can be realized as a Look-Up Table (LUT), allowing fast

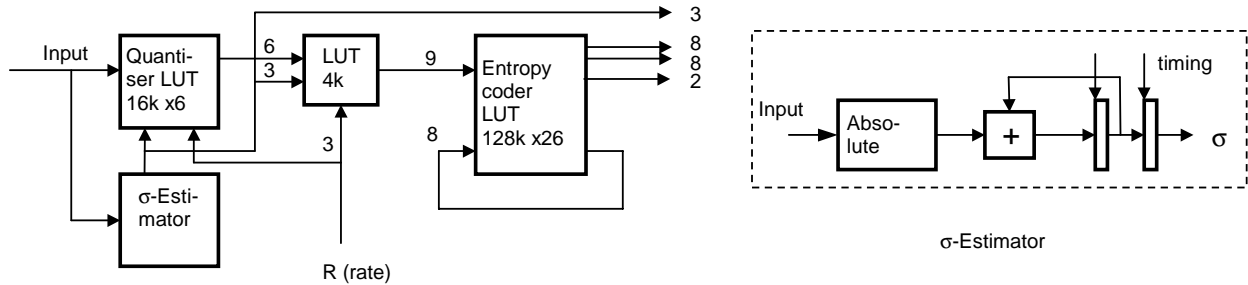


Fig. 6 SAR Compressor Architecture (ROI control not shown)

and simple implementation structures [9]. In its simplest and most straight forward form, the quantiser is a LUT with the following input variables: one sample (8 bits), the standard deviation σ of the current block, and the output rate parameter R.

The entropy coder can be realised as a Finite State Machine (FSM) with 255 states. A transition to a state can result in 0, 1, or 2 byte-sized codewords. This technique avoids time consuming bit-slice processing. The output of the LUT consists of 26 bits: 16 bits so that maximally two byte-sized codewords are generated, the 8-bits FSM state, and a 2 bits parameter to indicate the number of current output bytes. Both the LUTs operate with a clock rate equal to the sample rate. The σ -estimator calculates the standard deviation of blocks of $N = 32, 64$ or 128 samples. For 8-bits data with a Gaussian distribution and with saturation thresholds ± 127 , the relation between standard deviation and mean absolute value is

$$Mean|I| = Mean|Q| = 127.5 - \sum_{i=0}^{127} erf\left(\frac{i+1}{\sigma\sqrt{2}}\right)$$

In other words to reduce the complexity it is possible to derive the standard deviation of a block from the mean of the samples of the block. Figure 6 shows a more detailed version of the architecture.

The LUT structures are suitable for application in a number of random access memories (RAM) complemented with some circuits. The advantage is that a high-speed pipeline configuration can be achieved. Obviously, the RAM contents have to be loaded upon power-up with a dedicated controller or by an external process. The system should further be extended with EDAC circuitry to protect the RAMs against soft errors due to radiation.

Basically, the ECBAQ compressor can be implemented with one FPGA device and four 128 Kbytes RAM devices. An FPGA (Field Programmable Gate Array) is a type of gate array where the interconnection between gates can be defined by programming the complete packaged device. With the current generation of radiation-tolerant FPGA's a throughput of over 100 MC/s is not yet possible unless parallelisation would be applied to increase the compressor speed at the cost of additional logic. For applications with a speed requirement lower than 50 MC/s, the FPGA solution is the most attractive technique. After completing and finalizing such a design, for really high-speed applications the design can be converted into an ASIC. However the baseline should be FPGA to keep the cost of the development cycle low.

VII. CONCLUSIONS

Future operational SAR missions require data compressors with higher compression ratio and more flexibility. In this respect Entropy-Constrained Block Adaptive Quantisation is an attractive option compared to BAQ, because

- ECBAQ outperforms BAQ with respect to the Signal to Quantisation Noise Ratio,
- ECBAQ is rate programmable (non-integer rates)

It is demonstrated that a space borne ECBAQ compressor featuring region-of-interest coding can be implemented with a complexity that is more or less similar to BAQ.

ECBAQ can be combined with a frequency filtering pre-processor to further increase the compression ratio.

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