DPCM COMPRESSION OF SAR RAW DATA

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ABSTRACT

In this paper we investigate the use of DPCM compression for SAR raw data. We apply results from Wiener theory to analyze the statistics of SAR raw data. On the basis of this analysis, a DPCM-based compression algorithm named DPCM-BAQ is proposed. The performance of this algorithm is compared with that of BAQ, showing a significant improvement. Overall, in the cases considered, DPCM-BAQ achieves SNR in excess of up to 2.4 dB with respect to BAQ.

1 INTRODUCTION

Synthetic Aperture Radar (SAR) systems have attracted a considerable interest in civilian and military applications, due to their ability to remotely acquire data under any weather condition. Satellite and airborne SAR operate by emitting radiofrequency pulses at given time instants (i.e. spatial locations), and sampling the in-phase and quadrature components of the echoes scattered by ground targets and gathered at the receiver antenna. Such received data are usually organized into a two-dimensional matrix of complex numbers, where the two variables are the slant range and azimuth coordinated of each target, and the real and imaginary part of each coefficient represents the in-phase (I) and quadrature (Q) part of the received signal; these data are commonly referred to as SAR raw data. In satellite systems it is usually necessary to transmit the raw data to a ground station via a dedicated link. At this stage, the raw data can be transformed into a complex image by means of a focusing procedure, which is often computationally intensive.

A known issue with SAR systems is that they collect a huge amount of raw data, thus imposing to resort to lossy data compression in order to match the downlink capacity; on the other hand, the (usually) very limited on-board computational resources call for very simple compression schemes. Several algorithms have hence been proposed to compress these data. Many of them are based on the popular Block Adaptive Quantization (BAQ) scheme [1] and on its variant Flexible-BAQ (FBAQ) [2], which have been employed in the Magellan and Envisat missions respectively. These algorithms achieve a good trade-off between performance and complexity, and have thus become *de facto* standards. They have also been used in conjunction with vector quantizers [6] and trellis-coded quantizers [4]; however, the additional complexity hardly repays the moderate performance improvement. Some attempts to apply the transform coding paradigm to SAR raw data has also been made in [6, 7] using FFT, DCT, wavelets and wavelet packets; trellis-coded quantization after range focusing has also been proposed [5]. Although interesting results have been obtained, in this cases the computational issue becomes a major one, and may hinder the use of such techniques in real-world applications.

Most SAR data compression algorithms are mainly designed to exploit the first-order statistics of the raw data. In a way, it is generally accepted that the second-order statistics are very difficult to model; this is substantiated by the fact that those algorithms which exploit SAR raw data correlation are based on transform coding, whose main ability is to capture the redundancy of large classes of signals without requiring explicit second-order modelling. In this paper, following an idea in [6], we present some results on second-order modelling of SAR raw data and quantizer design; these results are used to design a DPCM-based compression algorithm, which achieves very satisfactory results in terms of performance and complexity.

2 SAR RAW DATA STATISTICAL MODEL

2.1 First-order statistics

It is well-known that the I and Q components of the SAR raw signal can be accurately modelled as zero-mean Gaussian independent processes; their non-stationarity is due to the slow variation of the standard deviation in range and azimuth. Thus, on reasonably small $N \times N$ data blocks (say $N = 32$), the raw signal can be regarded to as a stationary Gaussian process.

It is worth remarking that, in the majority of SAR

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systems, the raw data undergo A/D conversion prior to possible compression and transmission. The quantization is typically done with a number of bits from 4 to 8 according to the signal-to-noise (SNR) ratio at the receiver. This involves that, especially for the coarsest quantization, the statistics of the resulting signal may depart from Gaussian, in that the tails of the distribution may be truncated. This has some effect on quantizer performance, as will be shown in Sect. 2.3.

2.2 Second-order statistics

There are two approaches in dealing with correlation of SAR raw data. The approach in [7] assumes no explicit knowledge of second-order statistics, and uses compactly supported basis functions (e.g. wavelets or wavelet packets) to represent the non-stationary SAR signals. Conversely, the approach in [6] recognizes that, if the SAR raw signal is blockwise normalized, its power spectral densities (psd) in the range and azimuth directions are related to the SAR system parameters; this can be exploited to design compression algorithms that exploit this knowledge.

In this paper we follow this second approach. However, unlike [6], we avoid to employ computationally expensive signal transforms, but rather attempt to make explicit use of the correlation model in a DPCM-based scheme. In particular, the approach in [6] is based on the idea of normalizing the I and Q components of the SAR signal in such a way that each $N \times N$ block has unit energy. In this way, it is known [6] that, on sufficiently large data vectors,

1. the signal psd in the range direction is dictated by the chirp bandwidth, e.g. it can be approximated as a window function with support equal to the two-sided span of the transmitted linear chirp, which generally occupies a large portion of the frequency spectrum of the sampled SAR signal;

2. the signal psd in the azimuth direction is proportional to the azimuth antenna pattern.

In order to understand how much the SAR signal is correlated in either direction, one can evaluate the *spectral flatness measure* γ_X^2, which is defined for a zero-mean random field X as [3]

$$\gamma_X^2 = \frac{\exp\left[\frac{1}{2\pi}\int_{-\infty}^{\infty}\log_e S_{XX}\left(\mathrm{e}^{\jmath\omega}\right)d\omega\right]}{\sigma_X^2} = \frac{\eta_X^2}{\sigma_X^2}$$

being $S_{XX}\left(\mathrm{e}^{\jmath\omega}\right)$ the psd of X and σ_X^2 its variance. The allowed range is $0 \leq \gamma_X^2 \leq 1$, with $\gamma_X^2 = 1$ for a white noise process. The inverse γ_X^{-2} is also called *waveform predictability*; moreover, η_X^2 is recognized as the minumum prediction error variance for X when the predictor order approaches infinity. A result from Wiener theory states [3] that a random process with $S_{XX}(\mathrm{e}^{\jmath\omega}) = 0$ over a finite interval is predictable with zero error, i.e. $\gamma_X^{-2} \to \infty$. Now we recognize that, in the context of SAR raw data, this is the case of the range psd, which can be approximated to a certain extent as a window function. As a result, Wiener theory lets us suppose that the SAR raw signal is more predictable in range rather than in azimuth. It will be shown in Sect. 4 that this is verified in practice. Moreover, the very large extent of the support of the range psd also involves that the range correlation is a short-term one. This means that a linear predictor with few taps can effectively act as decorrelation stage.

2.3 Quantizer design

SAR signal compression algorithms such as BAQ exploit the Gaussian signal statistics by employing a pdf-optimized non-uniform Lloyd-Max quantizer [3]. The quantizer thresholds are computed so as to maximize SNR for a unit variance Gaussian process, and are multiplied by the estimated variance of each data block. We argue here that this quantizer is slightly suboptimal, especially in the case of raw data that have been prequantized on few bits (e.g. the 4-bit or 6-bit modes of the SIR-C/X-SAR mission); in fact, the quantizer overload error is negligible, since the true distribution lacks the tails due to the overload of the A/D converter. Even more interestingly, we have found that this suboptimality is partially solved by DPCM, since it tends to restore the pdf tails by obtaining the output samples as linear combination of the Gaussian input samples.

3 PROPOSED ALGORITHM

The compression algorithm proposed in this article aims at demonstrating the ability of DPCM to capture the correlation of SAR raw data. It consists of two stages.

1. The first stage normalizes the amplitude of the input signal, by considering non-overlapping $N \times N$ signal blocks of the I and Q samples, and dividing each coefficient in the block by the standard deviation of the samples in the block.

2. The second stage operates on the normalized samples of each block, and performs DPCM compression with a Lloyd-Max quantizer in the feedback loop (see Fig. 1). DPCM is performed in either range or azimuth. Extension to the 2-D case is left for future work.

As for the first stage, it is worth noticing that, when complexity is a major issue, data normalization can be done by reusing existing low-complexity blocks, e.g. by applying the BAQ quantizer with a high number of bits per sample, as in [6].

As for the DPCM stage, the SAR raw data compression algorithm proposed in this paper is based on an autoregressive (AR) model of the input. The prediction order is referred to as p, and its influence on the compression performance is investigated. The AR model

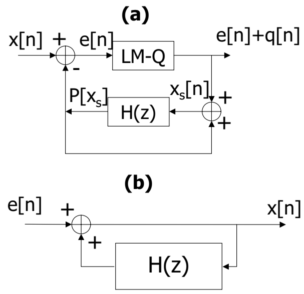

Figure 1: (a) DPCM encoder with Lloyd-Max quantizer in the feedback loop; (b) DPCM decoder with inverse prediction error filter

parameters are estimated from the data following the classical method described in [3], to estimate the linear predictor $H(z)$. Fig. 1 shows the block scheme of a typical DPCM encoder and decoder. In particular, we have used the encoder with quantizer in the feedback loop as in Fig. 1-a, in such a way that the encoder prediction loop works on the same quantized signal available at the decoder. Since the prediction error is a linear combination of Gaussian random variables, it is Gaussian too. Therefore a Lloyd-Max quantizer for Gaussian pdf, is used in the feedback loop. Since the proposed algorithm operates on data blocks, it has been called DPCM-BAQ.

4 EXPERIMENTAL RESULTS

The performance of the DPCM-BAQ algorithm has been evaluated on real-world SIR-C/X-SAR raw data. These data are preliminary quantized on 4 and 6 bit/sample. We have selected two scenes, named *Jesolo* and *Innsbruck*, which are quantized on 6 bit/sample, and tested the BAQ and DPCM-BAQ algorithms at rates of 2 and 3 bit/sample. Results are reported in case of range and azimuth decorrelation respectively, and are parameterized on the prediction order used in the DPCM scheme. Data normalization has been made on 32×32 blocks. The selected quality metric is SNR between the original and decoded raw data.

4.1 Range decorrelation

The performance of the BAQ and DPCM-BAQ algorithms in case of 3-bit quantization and range decorrelation is shown in Fig. 2. As can be seen, the BAQ performance for the *Innsbruck* image is very close to the theoretical maximum SNR of the 3-bit Lloyd-Max quantizer, i.e. 14.62 dB. A SNR gap can be noticed in the *Jesolo* image, which can be explained by the fact that this image is taken over sea, and hence has few scatterers; thus the noise statistics slightly departs from Gaussian. In any case, it is worth noticing that the performance of the DPCM-BAQ algorithm is significantly better than BAQ. Interestingly, the SNR performance of DPCM-BAQ is less dependent on the scene

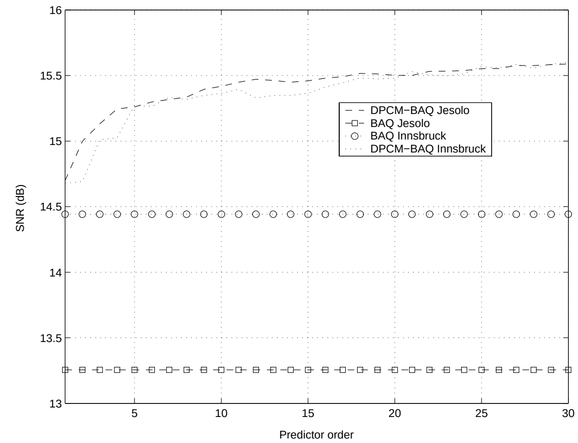

Figure 2: BAQ and DPCM-BAQ performance (range) at 3 bit/sample for *Jesolo* and *Innsbruck*

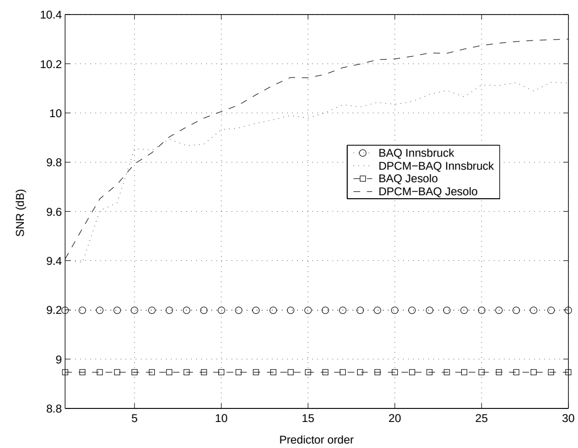

Figure 3: BAQ and DPCM-BAQ performance (range) at 2 bit/sample for *Jesolo* and *Innsbruck*

content than that of BAQ. In fact, even though the raw data are not perfectly Gaussian, the prediction error is Gaussian to a better approximation, since it is obtained as a linear combination of identically distributed quasi-Gaussian random variables. As expected, similar results hold for 2-bit quantization, and are reported in Fig. 3. The DPCM-BAQ gain reaches up to 2.4 dB in the 3-bit case, and 1.4 dB in the 2-bit case, at a maximum prediction order of 30.

4.2 Azimuth decorrelation

Similar performance curves have been obtained by running the DPCM algorithm in the azimuth direction. The results in case of 3-bit and 2-bit quantization are reported in Fig. 4 and 5 respectively. As can be seen, also in this case the DPCM-BAQ algorithm exhibits a significant performance gain with respect to BAQ, with a maximum of 2.1 dB in the 3-bit case, and 1.5 dB in the 2-bit case. However, the DPCM-BAQ performance gain is slightly less than in case of range operation; this is

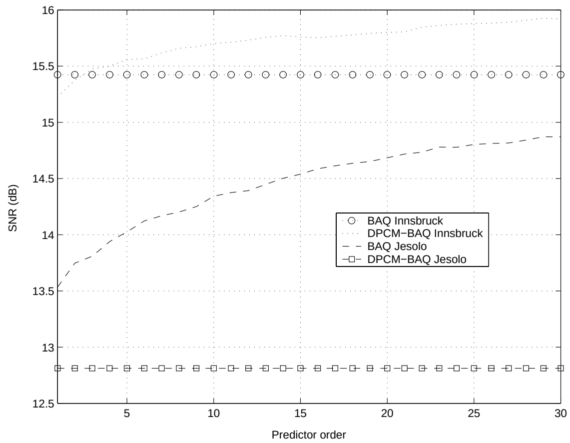

Figure 4: BAQ and DPCM-BAQ performance (azimuth) at 3 bit/sample for *Jesolo* and *Innsbruck*

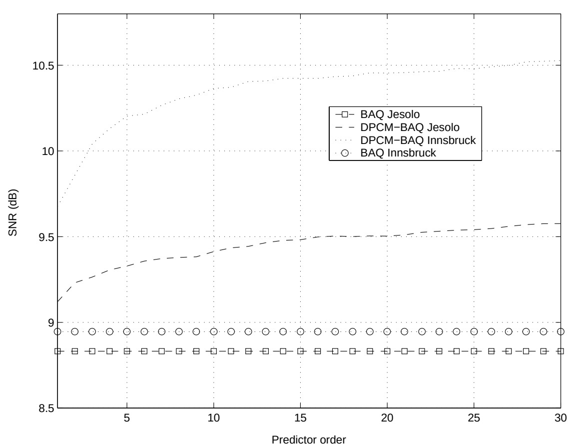

Figure 5: BAQ and DPCM-BAQ performance (azimuth) at 2 bit/sample for *Jesolo* and *Innsbruck*

in accordance with the theoretical results in Sect. 2.2, stating that the SAR signal is less predictable in the azimuth than in the range direction.

4.3 Discussion

Several remarks can be made on the basis of the comparative results presented above. Firstly, it can be seen that the overall SNR performance of the DPCM-BAQ algorithm is significantly better than that of BAQ. Secondly, the results substantiate the deduction, based on Wiener theory, that the data are better predictable along the range rather than the azimuth coordinate. This greatly facilitates data compression, since in SAR systems data are sampled by range lines; no complicated buffering is hence necessary for rangewise coding. Thirdly, with respect to other algorithms such as those in [6, 5, 7], the DPCM-BAQ exhibits a very low computational complexity, which can be compatible with on-board computational facilities of SAR platforms. Besides, it has turned out that the performance of the DPCM-BAQ algorithm is little dependent on the scene content, mainly due to the fact that the prediction error tends to be "more Gaussian" that the raw data. For these reasons, DPCM-BAQ can represent an advantageous choice for on-board compression of SAR raw data. Finally, the experimental results presented in Sect. 4 have been obtained by using the optimal predictor at the encoder and the decoder, recomputed for each range and azimuth line. However, preliminary results indicate that using the *same* predictor, computed once and for all, for all range or azimuth lines, causes a very limited performance loss, while greatly reducing the number of operations to be done at the encoder; this is in agreement with the observation that, after normalization, the SAR raw signal is stationary in both range and azimuth.

5 CONCLUSIONS

In this paper we have presented a DPCM-based algorithm for range and azimuth compression of SAR raw data. We have shown that the overall performance of the proposed algorithm is significantly better than that of BAQ. Yet, there is still room for improvements to the DPCM-BAQ algorithm. Firstly, 2-D prediction could be used in place of one-dimensional DPCM. Secondly, since after normalization the second-order statistics of the raw data is known, one could design the range and azimuth predictors once and for all, with the aim of maximizing performance and minimizing complexity, e.g. choosing only rational coefficients for the predictors, so that a fixed-point implementation can be used instead of a floating-point one.

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