Predictive Quantization for Onboard Data Reduction in Future SAR Systems

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Abstract

Next-generation satellite SAR systems will provide unprecedented high-resolution data products thanks to multi-static configurations, wider swath widths, and multiple polarizations. As a drawback, a considerable amount of onboard data is going to be generated, leading to onboard storage and downlink capacity challenges. In this context, the need for an onboard compression technique featuring low memory requirements and low complexity is of great interest, due to the strict hardware and cost constraints of satellite platforms. In this paper, an investigation of predictive coding applied to SAR systems is carried out. Specifically, two types of novel predictive encoders are presented: Dynamic Predictive BAQ (DP-BAQ) and Non-Causal Predictive BAQ (NC-PBAQ). A theoretical investigation is initially introduced and the results are finally reported by taking into account the trade-off between data reduction performance and computational requirements. DP-BAQ gain in terms of data reduction is directly dependent on both the performance requirements and the system constraints (e.g. the antenna size), and has already been proven to reach 20-25% of data reduction for the case of DLR's Tandem-L mission proposal. The non-causality introduced by NC-PBAQ shows promising results with respect to the performance of DP-BAQ, at least from a theoretical point of view. Moreover, the computational effort required for DP-BAQ encoding is less demanding, therefore could be implemented in state-of-the-art spaceborne SAR systems.

1 Introduction

The upcoming spaceborne satellite SAR systems will feature advanced acquisition modes developed in recent years. In this study, we consider a SAR system operating in the Staggered SAR mode. A mission proposal composed by two twin satellites in L band frequency operating in Staggered SAR is Tandem-L. The goal of the mission is to monitor the Earth surface such as soil, ice, forest and ocean currents for a wide range of different applications [1]. Each of the two SAR sensors includes a 15 meter deployable reflector which, together with a digital beamforming phased array, allows the implementation of the so called SCan-On-REceive (SCORE) mode [2]. This will provide to the scientific community high resolution (7 m) wide swath (350 km) SAR products, being able to cover the entire globe roughly two times per week. According to the Staggered SAR principle [14], at each range position there will be some missing azimuth samples in the raw SAR data, due to the intrinsic design of the acquisition. Therefore, this detail must be taken into account in the design stage of data volume reduction strategies. With such acquisition capabilities, the handling of the data volume is challenging for both the onboard storage and the downlink capabilities. By exploiting state-of-the-art techniques such as the Block Adaptive Quantization [3], the amount of onboard data to be transmitted to Earth would be almost twice the available downlink capacity for the mission, which is 8 Terabytes/day for Tandem-L. A solution to this problem has been presented in [10], where a best linear unbiased interpolator has been applied together with an onboard azimuth filtering, implemented in order to reduce the data rate by up to 50% for the considered case. Unfortunately, such a technique, although very powerful, requires a high number of range lines to be stored on board before performing the filtering, reaching the limit of the hardware capabilities of the system [4].

Predictive quantization has been known in the signal processing literature for decades, and was originally implemented for speech coding [5]. In this paper predictive coding has been is investigated for data volume reduction in the context of Staggered SAR systems, due to its low complexity and memory requirements. Starting from Predictive BAQ (PBAQ) [12], a more challenging application of predictive coding is presented (DP-BAQ), where the main focus relies on performance optimization. Moreover, we also propose a Non-Causal Predictive BAQ, aiming at compressing the SAR raw data in a simple and effective way, only at the cost of a considerable increase of the system complexity in the decoding phase. Since the computational power available on ground consists of high-end CPUs, this solution does not represent a limitation. The idea to include the non-causality in the encoding system allows, at least from a theoretical point of view, for doubling the performance of DP-BAQ. The paper is structured as follows: Section 2 provides an overview on SAR raw data quantization. Section 3 describes the Dynamic Predictive Block Adaptive Quantizer (DP-BAQ) together with its mathematical formulation, while in Section 4 the Non-Causal Predictive Block Adaptive Quantizer (NC-PBAQ) is defined. The results of Monte Carlo simulations are reported in Section 5 while conclusions and outlook are drawn in Section 6.

2 SAR Raw Data Quantization: Background

Onboard SAR raw data consists of a complex matrix where the value of each pixel represents the coherent backscatter radar power from targets illuminated within the antenna beamwidth. Due to the low correlation of the raw data matrix samples, onboard data compression is a highly challenging topic, since the available memory and the downlink capabilities are limited. Operative SAR systems such as TerraSAR-X and TanDEM-X are equipped with a Block Adaptive Quantizer (BAQ). It is a quantization scheme which allows for a fair trade-off between SAR products quality and resulting volume of data [3], [7]. BAQ groups a number of samples within blocks and adapts the decision levels of the quantizer to each block statistics [3], [8]. The introduced complexity of this technique is rather low, featuring a considerable advantage in the trade off with encoding performance. The typical implementation of the BAQ is through a Cartesian quantizer, thus treating the Inphase (I) and Quadrature (Q) components of the signal as independent ones during the encoding procedure. This assumption is theoretically correct since the two components of the raw data samples are statistically independent Gaussian variables.

3 Dynamic Predictive Block Adaptive Quantization (DP-BAQ)

The application of predictive coding for SAR raw data compression has been firstm introduced in [11], and then further elaborate in [12][13]. It consists of a linear prediction along the azimuth domain, assuming a certain gain if specific assumptions apply. Linear Predictive Coding (LPC) [5] is considered along the azimuth direction. The key feature of this technique is the encoding of the difference between the data and its prediction. This allows a reduction of the dynamic range of the signal, thus a lower amount of encoding bits. The prediction consists of a linear combination of the N preceding samples, where N defines the *order* of the predictor. Being $\tilde{s}[\mathrm{n}]$ the prediction of $s[\mathrm{n}]$ from N previous samples, it can be expressed as

$$\tilde{s}[\mathrm{n}] = \sum_{i=1}^{N} \beta_i \left(s[\mathrm{n}-i] + e[\mathrm{n}-i] \right), \tag{1}$$

where β_i represents the weight assigned to every i-th previous sample and $e[\mathrm{n}-\mathrm{i}]$ is the quantization error for the i-th previous sample. Considering (1) as the prediction of one single azimuth sample, the encoded signal will be the difference between the actual sample value $s[\mathrm{n}]$ and its prediction

$$s_{\mathrm{d}}[\mathrm{n}] = s[\mathrm{n}] - \tilde{s}[\mathrm{n}]. \tag{2}$$

The weights β_i are computed during the system design stage from the autocorrelation function of the signal. The formulation seeks for the best set of weights which minimizes the prediction error. The variance of the difference signal can be expressed as

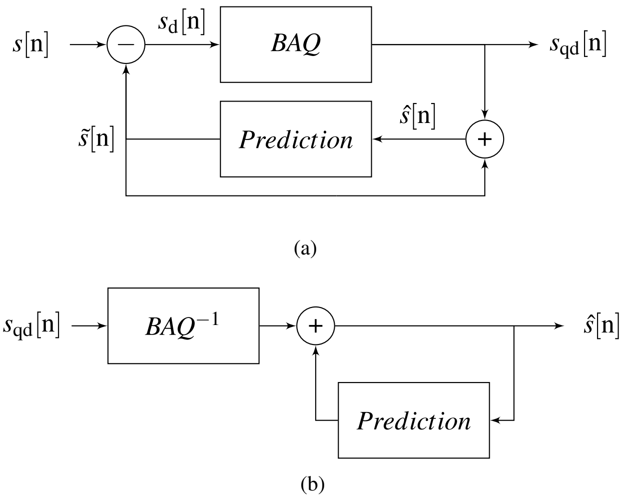

Figure 1 Predictive quantization encoding (a) and decoding (b) flow schemes.

$$\sigma_{\mathrm{d}}^2 = E\left[s_{\mathrm{d}}^2[\mathrm{n}]\right] = E\left[(s[\mathrm{n}] - \tilde{s}[\mathrm{n}])^2\right]. \tag{3}$$

It is possible to derive the set of weights that minimizes the MSE [5]

$$\boldsymbol{\beta} = \boldsymbol{C}^{-1}\boldsymbol{\rho} \tag{4}$$

where $\boldsymbol{\beta}$ is the unknown weights vector, $\boldsymbol{C}$ is the correlation matrix between the N previous samples used for the prediction, and $\boldsymbol{\rho}$ is the vector of the correlation between the N previous samples and the sample to be predicted.

3.1 Theoretical Gain

The coding gain G_{P} in LPC is known as the ratio between the variance of the input signal s and the one of the prediction error s_{d}

$$G_{\mathrm{P}} = \frac{\sigma_{\mathrm{s}}^2}{\sigma_{\mathrm{d}}^2}. \tag{5}$$

This means that a more limited signal dynamic after predictive coding leads to a higher gain [6]. Since SAR raw data are approximated by a zero-mean circular Gaussian process, it is possible to express the difference between N Gaussian variables (see (1)) still as a Gaussian random variable. This allows one to mathematically express the expected gain by estimating the standard deviation of the differential variable σ_{d}^2 for a given set of system constraints. In Figure 3, the theoretical gain curves are plotted as a function of the pulse repetition frequency (PRF). For the mean PRF of Tandem-L the expected gain is about 5 dB for the 4$^{\text{th}}$ order predictor.

3.2 Implementation

BAQ operates in blocks of samples within the same range line. For the case of TerraSAR-X and TanDEM-X one block consists of 128 samples. The fusion between LPC and BAQ is made by considering the prediction process of an entire range line and then applying BAQ to it. A block length of 128 samples has been considered, and the encoding scheme depicted in Figure 1(a) shows how the BAQ operates in the process. Figure 1(b) shows the block diagrams for the decoding operation [6]. The whole process is known to be coherent as it takes into account the quantized difference for the prediction both in encoding and decoding, making possible the exact same prediction system both on board and on ground.

3.3 Gap mitigation

The techniques we are presenting are applicable to future SAR systems featuring a suitable constraint (e.g. sufficient sampling in azimuth). One possible system is the Staggered SAR, which brings also as an issue blind ranges [14]. As introduced in [12], the location of blind ranges along the azimuth domain is known at system design level. This allows one to adapt the prediction process as a function of the gap positions. We introduce here an optimised configuration named "Dynamic". Our analysis showed significant losses in the presence of gaps if we consider a pure 4$^{\text{th}}$ order predictor. Thus, we propose to encode the subsequent sample of a gap with a direct BAQ (no prediction is in charge), then perform a 1$^{\text{st}}$ order prediction for the following sample and so on. The increase of the prediction order at each sample is done till the designed prediction order for the system is reached. Moreover, in order to recover the missing information in the blind range position, we also suggest to increase the bit rate before and after the gap position for having a finer representation to be exploited during the interpolation process. The latter is performed on-ground before the focusing operation [12]. Given a bit rate of N_{b} bits/sample, we exploit the remaining N_{b}, which are not used for the gap, for the adjacent samples. The complete scheme of the DP-BAQ is depicted in Figure 2, showing both the variable bit rate and the dynamic prediction process. This technique features a signal representation performance in vicinity of the gaps in the interpolated data comparable to the other gap-free portions of the signal.

4 Potentials for Non-Causal Predictive Block-Adaptive Quantization

In the previous section we have considered a prediction process which takes into account the previous samples to predict the subsequent one. This formulation is known in literature as "causal" system. Looking for an even more efficient system, it is possible to consider a "Non-Causal" prediction process, by performing a prediction on the basis of past and future (subsequent) samples [15]. We will refer to this specific technique as Non-Causal Predictive Block Adaptive Quantization (NC-PBAQ). For this case, the prediction is then described as

$$\begin{aligned}\tilde{s}[\mathrm{n}] = &\sum_{i=1}^{N/2} \beta_i \left(s[\mathrm{n}+i] + e[\mathrm{n}+i]\right) + \\ &\sum_{i=1}^{N/2} \beta_i \left(s[\mathrm{n}-i] + e[\mathrm{n}-i]\right).\end{aligned} \tag{6}$$

The encoded sample is still expressed as

$$s_{\mathrm{d}}[\mathrm{n}] = s[\mathrm{n}] - \tilde{s}[\mathrm{n}]. \tag{7}$$

We will now focus on the encoding and decoding formulation of the 2$^{\text{nd}}$ order non-causal predictor (exploiting one previous and one subsequent sample). Equation (6) and (7) can also be expressed in matrix notation:

$$\boldsymbol{E}\boldsymbol{s} = \boldsymbol{d}, \tag{8}$$

where $\boldsymbol{E}$ is the encoding matrix containing the weights β_i, $\boldsymbol{s}$ is the samples vector and $\boldsymbol{d}$ is the vector of the prediction error. It is worth noting that the quantization error has been neglected as the reconstructed samples are not available at the encoding phase. By inverting the upper formula we can derive the decoding operation, expressed as:

$$\boldsymbol{E}^{-1}\boldsymbol{d} = \bar{\boldsymbol{x}}, \tag{9}$$

where $\bar{\boldsymbol{x}}$ denotes the reconstructed samples vector. As the encoding matrix is invertible since it is a banded Toeplitz matrix featuring N sub-diagonals, the encoded signal can be correctly reconstructed provided that no addition error sources are considered. If we include the quantization in the encoding process, as this represents the actual case for SAR raw data, the decoded signal does not match anymore with the encoded one due to accumulation errors introduced in the quantization process. This is mainly due to the fact that the closed loop operation depicted in Figure 1(a), which allows to perform the prediction with reconstructed samples (available on ground), is not implementable in a straightforward manner. Moreover, the decoding matrix $\boldsymbol{E}^{-1}$ does not feature any zeros, thus the quantization error of each sample is linearly combined in the prediction of all samples, causing more noise in the decoding operation. Preliminary investigations have shown that the matrix inversion itself gets more computational demanding as the sample vector increases. In our analysis we observed that this leads to an encoding result which does not satisfy the theoretical expectations. The assumption that the raw data samples can be represented by a zero-mean circular Gaussian distribution still holds, thus one can derive the dynamic reduction σ_d and the resulting gain G_{NC} in the same way as done for the causal encoding scheme for a given set of system constraints.

5 Results

As briefly introduced in Section 1, we take as reference system Tandem-L in order to fix a scenario in order to validate our method. Table 1 summarizes the main parameters of the considered system. For this configuration, a 4-bit

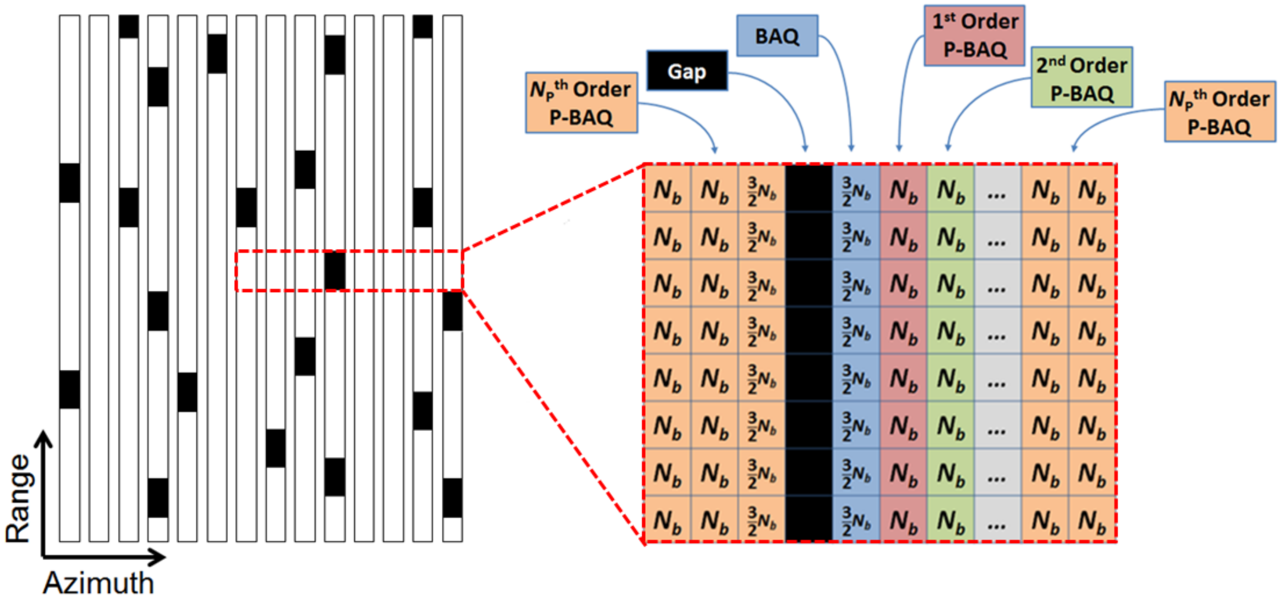

Figure 2 (Left) Typical distribution of the gaps (black rectangles) within a staggered SAR acquisition. Each blind range typically extends by hundreds of samples in the range direction but only one sample in the azimuth direction. (Right) Zoom-in of a raw data matrix with gaps. Each cell corresponds to a complex raw data sample. The proposed method is implemented by varying the bit rate allocation (indicated in each box, where N_b represents the mean bit rate in bits/sample) together with a dynamic prediction order (highlighted by colors and shown on the top of the figure) in the gap vicinity.

Table 1 Tandem-L system parameters.

Parameter	Value
Orbit altitude	745 km
Horizontal baselines	800 m . . . 20 km
Inclination	98.4°
Revisit time	16 days
Frequency	L band
Range bandwidth	up to 84 MHz
Azimuth resolution	7 m
Swath width	175 km . . . 350 km
Downlink capacity	∼8 Terabytes/day
Look direction	left/right
Reflector diameter	15 m
Lifetime of mission	10 years
Polarization	single/dual/quad

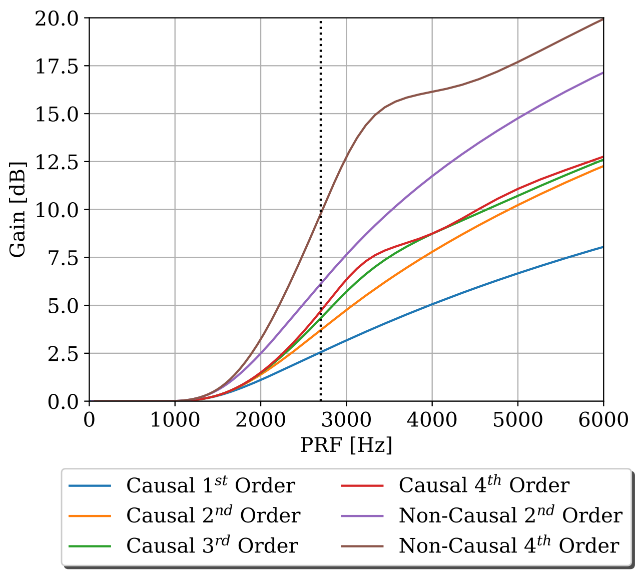

Figure 3 Theoretical gain in dB for Causal and Non-Causal predictive coders as a function of the PRF. The dotted line refers to the PRF required for Tandem-L.

BAQ is required for guaranteeing a low interferometric coherence loss of about 1% [9]. This constraint is directly related to the quantization errors themselves, as an error in the discretization of the samples is associated to an error in the phase of the focused image. The correlation introduced by the antenna pattern is enough to implement such a technique, as an oversampling is necessary due to the operation in the Staggered SAR mode [14]. The Tandem-L mission features a reflector antenna (see Table (1)), but in this paper an approximation to a planar array with uniform aperture and azimuth length L=10 m has been considered, which allows for the description of the antenna pattern with a standard *sinc* function. In Figure 3 we report the expected theoretical gain as a function of the PRF for both DP-BAQ and NC-PBAQ. In order to verify the implementation of the causal and non-causal encoding techniques, we have performed several Monte-Carlo simulations. As introduced in Section 4, the practical implementation of the NC-PBAQ affected by quantization noise brings an accumulation of error leading to mismatch between the encoded and decoded signal. Therefore, in this section we will focus on the DP-BAQ encoding capabilities. The quantitazion error

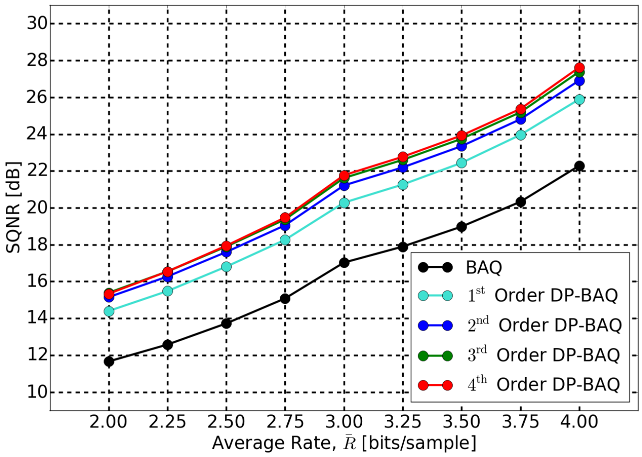

Figure 4 Signal-to-Quantization Noise Ratio of DP-BAQ at different orders of prediction as a function of the bit rate.

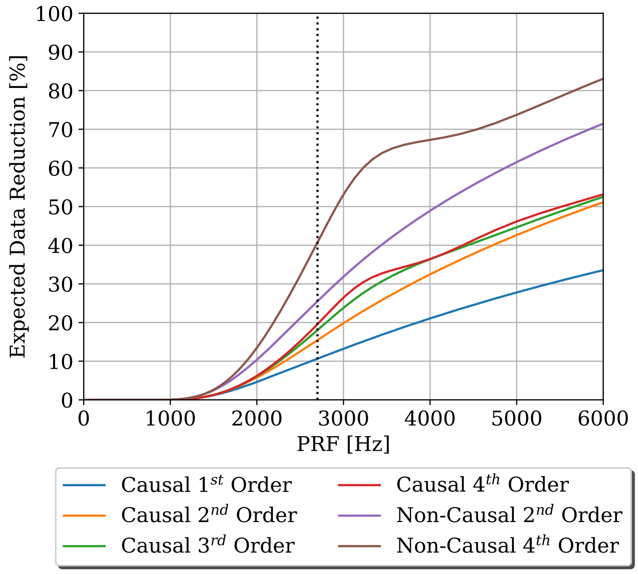

Figure 5 Expected data reduction performance as function of the PRF. The considered reference bit rate is 4 bps.

can be expressed as $q = s - s_q$, thus the difference between the uncompressed signal and its quantized version s_q. The effective data reduction capability must be verified at the end of the SAR processing chain, i.e., after the focusing operation. The performance parameter which assess the encoding quality is the Signal-to-Quantization Noise Ratio (SQNR), defined as

$$\mathrm{SQNR} = \frac{\sum_{i=1}^{I} |x_i|^2}{\sum_{i=1}^{I} |q_i|^2}, \tag{10}$$

where I represents the total number of azimuth samples, x is the received signal before the quantizer, and q is the quantization error. In Figure 4 the SQNR for the DP-BAQ is depicted for different bit rates as well as for the state of the art BAQ. One can notice that the performance for the BAQ at 4 bps ($\sim$22 dB) is approximately equivalent to the 4$^{\text{th}}$ order DP-BAQ at 3 bps. Hence, a $\sim$25% data reduction is observed for the considered system constraints.

It is possible to define the data reduction for the 4 bit/sample case as:

$$\mathrm{DR}_{\%} = \frac{G_{\mathrm{dB}}}{G_{1\text{-bit}}} \cdot \frac{100}{4}, \tag{11}$$

where G_{dB} and $G_{1\text{-bit}}$ represent the gain in dB for a given encoding technique and the approximated gain for an increase of 1 bit per sample in the encoding (normally around 6 dB), respectively. The factor 100 stands for the percentage expression and 4 is the designed bit rate for the state-of-the-art reference technique (i.e. BAQ). In Figure 5 the expected data reduction is reported as a function of the PRF for all the proposed techniques. We have considered for the G_{dB} factor the theoretical curves depicted in Figure 3.

6 Discussion and Conclusions

In this paper novel raw data encoding techniques for SAR systems have been investigated. The goal of the paper is to present encoding systems featuring satisfying performance, together with low computational burden and onboard memory consumption. The expected theoretically derived performance of the first technique (DP-BAQ) has been verified through Monte-Carlo simulations, showing a data reduction capability of 20-25% with respect to the state-of-the-art technique (BAQ). The proposed method requires a linear combination of previous samples (up to 4) and pre-computed weights. Moreover, for the investigated case of Tandem-L, the required memory consumption is only $\sim$25% of the technique proposed in [10] (4 range lines to perform prediction instead of around 16 to perform azimuth filtering). Another advantage with respect to [10] is the availability of the complete SAR raw data on ground, leaving room for further investigations and post-processing algorithms. However, the DP-BAQ is still not comparable in terms of data reduction capabilities with [10], but it is an interesting alternative thanks to its low complexity, which is a desired feature in satellite systems. Potentials for a new technique exploiting Non-Causal prediction had been introduced from a theoretical point of view, showing the capability to double the performance of DP-BAQ. Nevertheless, the implementation of the encoder and the decoder through matrix inversion leads to a higher computational complexity and, at the current state, unsatisfying results. Future work will focus on a coherent and more complete formulation of the non-causal problem aiming at finding a suitable practical realization and verification trough Monte-Carlo simulations.

7 Literature

[1] A. Moreira, G. Krieger, I. Hajnsek, K. Papathanassiou, M. Younis, P. Lopez-Dekker, S. Huber, M. Villano, M. Pardini, M. Eineder, F. De Zan and A. Parizzi, "Tandem-L: A highly innovative bistatic SAR mission for global observation of dynamic processes on the Earth's surface", IEEE Geoscience and Remote Sensing Magazine, Vol. 3 No.7, 2015, pp. 8-23

[2] G. Krieger, M. Younis, N. Gebert, S. Huber, F. Bordoni, A. Patyuchenko and A. Moreira: “Advanced digital beamforming concepts for future SAR systems”, Proceedings of International Geoscience and Remote Sensing Symposium (IGARSS), 2010, pp. 245-248

[3] D. C. Lancashire, B. A. F. Barnes and S.J. Udall, “Block adaptive quantization”, Google Patents, 2001, US Patent 6,255,987

[4] M. Pinheiro, P. Prats-Iraola, M. Rodriguez-Cassola and M. Villano, “Analysis of low-oversampled staggered SAR data”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, 2020, pp. 241-255

[5] N. Jayant and P: Noll, “Digital Coding of Waveforms–Principles and Applications to Speech and Video Englewood Cliffs”, 1984, New Jersey: Prentice-Hall

[6] A. Gersho and R.M. Gray, “Vector quantization and signal compression”, 2012

[7] R. Kwok and W. TK Johnson, “Block adaptive quantization of Magellan SAR data”, IEEE Transactions on Geoscience and Remote Sensing, 1989, Vol. 27, No. 4, pp. 375-383

[8] A. Moreira and F. Blaser, “Fusion of block adaptive and vector quantizer for efficient SAR data compression”, Proceedings of International Geoscience and Remote Sensing Symposium (IGARSS), 1993, pp. 1583–1585

[9] M. Martone, B. Bräutigam and G. Krieger, “Quantization effects in TanDEM-X data”, IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, No. 2, 2015, pp. 583-597

[10] M. Villano, G. Krieger and A. Moreira, “Onboard processing for data volume reduction in high-resolution wide-swath SAR”, IEEE Geoscience and Remote Sensing Letters, Vol. 13. No. 8, August 2016, pp. 1173-1177

[11] E. Magli and G. Olmo, “Lossy predictive coding of SAR raw data” IEEE Transactions on Geoscience and Remote Sensing, Vol. 41. No. 5, 2003, pp. 977-987

[12] N. Gollin, M. Martone, M. Villano, P. Rizzoli and G. Krieger, “Predictive Quantization for Staggered Synthetic Aperture Radar” In 2019 12th German Microwave Conference (GeMiC) (pp. 83-86). IEEE

[13] M. Martone, N. Gollin, M. Villano, P. Rizzoli and G. Krieger, “Predictive Quantization for Data Volume Reduction in Staggered SAR Systems”, IEEE Transactions on Geoscience and Remote Sensing, Vol. 58, No. 8, 2020, pp. 5575-5587

[14] M. Villano, G. Krieger, M. Jäger, and A. Moreira,“Staggered SAR: Performance Analysis and Experiments with Real Data”, IEEE Transactions on Geoscience and Remote Sensing, Vol. 55, No. 11, November 2017, pp. 6617-6638

[15] S. Ranganath, A. Jain, “Two-dimensional linear prediction models–part I: Spectral factorization and realization”, IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 33, No. 1, Feb 1985, pp. 280-299