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# On-Board Data Compression for Future SAR Systems: An Overview of the Research Activities at the Microwaves and Radar Institute of DLR

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## INTRODUCTION

Synthetic aperture radar (SAR) represents nowadays a well-established technique for a broad variety of remote sensing applications, being able to acquire high-resolution images of the Earth's surface, independently of daylight and weather conditions. In the last decades, innovative spaceborne radar techniques have been proposed to overcome the limitations which typically constrain the capabilities of conventional SAR for the imaging of wide swaths and, at the same time, of fine spatial resolutions. In addition to that, present and future spaceborne SAR missions are characterized by the employment of multi-static satellite architectures, large bandwidths, multiple polarizations, and fine temporal sampling. This inevitably leads to the acquisition of an increasing volume of on-board data, which poses hard requirements in terms of on-board memory and downlink capacity of the SAR system. This paper presents an overview of the efficient raw data quantization and data volume reduction methods which have been developed at the Microwaves and Radar Institute of DLR in the last years. In particular, we focus our attention on the exploitation of the use of artificial intelligence (AI), and in particular of deep learning (DL), with the goal of deriving an optimized and fully adaptive bitrate allocation to be used for raw data quantization, depending on a set of desired performance metric and requirements in the resulting focused SAR/InSAR products, without relying on a priori information on the acquired scene. The derived bitrate allocation maps (BRMs) is employed for adapting a state-of-the-art block-adaptive quantizer (BAQ) to the local characteristics of the input raw data and to the desired performance, and the results obtained on experimental TanDEM-X interferometric data demonstrate the potentials of the proposed method as a helpful tool for performance budget definition and data rate optimization of present and future SAR missions.
In the second part of the paper, we investigate and discuss potentials for data volume reduction in multi-channel SAR. These systems allow for high-resolution imaging of a wide swath but, on the other hand, require for their operation the acquisition and downlink of a huge amount of data: together with the intrinsic requirement related to resolution and swath width, this is due to the fact that the effective pulse repetition frequency (PRF) generated by the multiple channels is typically higher than the processed Doppler bandwidth, which introduces a certain oversampling in the azimuth raw data. Therefore, convenient data volume reduction strategies can be proposed, based on Doppler-based transform coding (TC) or linear predictive coding (LPC), which aim at exploiting the existing correlation between subsequent azimuth samples. We consider realistic multi-channel SAR system architectures, and simulate multi-channel raw data using synthetic as well as real backscatter data from TanDEM-X. We analyze the statistical properties (such as autocorrelation and Doppler power spectrum) exhibited by the multi-channel raw signal and discuss the impact of relevant system parameters, highlighting potentials and limitations of the proposed approaches in terms of achievable data volume reduction.
DLR is also member of the Consultative Committee for Space Data Systems (CCSDS) and the authors currently support the Data Compression Working Group with the main objective of defining and standardizing a data compression method for SAR systems. For this purpose, we carried out dedicated simulations and performance assessment on test (simulated as well as real SAR) data, which are also summarized in the last section of the paper. Finally, conclusions and outlook are provided.

## DEEP LEARNING FOR SAR RAW DATA QUANTIZATION

For present SAR missions, SAR raw data quantization is usually carried out by means of the Block-Adaptive Quantization (BAQ) [1]. In recent years, the principle of BAQ has been further developed resulting in novel algorithms, allowing for better performance and resource optimization. Specifically, one can recall acquisition-dependent compression schemes such as the Flexible Dynamic BAQ (FDBAQ) [2], which may even be combined with the implementation of non-integer data rates [3]. However, the FDBAQ performs a bitrate optimization based on the SAR raw data statistics only, while it does not consider the actual performance degradation in the final SAR products. The Performance-Optimized BAQ (PO-BAQ) [4] extends the concept of BAQ and represents the first attempt to optimize the resource allocation depending on

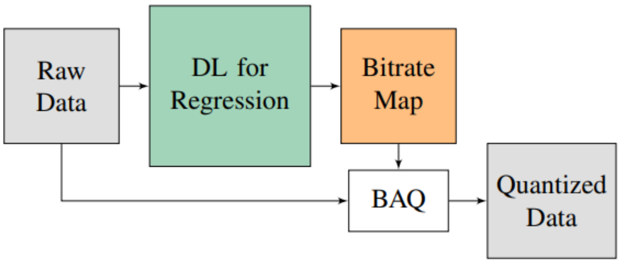



Fig. 1: Flow chart of the proposed method for a dynamic bitrate allocation using DL: the raw data matrix is provided to the trained DL model which predicts the required two-dimensional bitrate map (BRM), needed to achieve the desired performance. An adaptive quantizer (i.e., BAQ) performs the raw data encoding exploiting the estimated BRM.

the final performance requirement defined for the resulting higher-level SAR/InSAR product. In the specific, the PO-BAQ allocates at each portion of the scene the minimum number of bits which are satisfying a given performance quality on the final product. Quantization errors are significantly influenced by the local distribution of the SAR intensity [5] and, for this reason, PO-BAQ exploits the a priori knowledge of the SAR backscatter statistics of the imaged scene in the form of, e.g., look-up tables (LUTs) or backscatter maps [4]. This limitation results in further complexity and does not allow the method to be completely adaptive with respect to the acquired raw data, since the quantization settings are derived from prior considerations and do not account for the local conditions at the time of the acquisition. In this scenario, Artificial Intelligence (AI) represents one of the most promising approaches in the remote sensing community, enabling scalable exploration of large dataset and bringing new insights on information retrieval solutions [6]. In particular, convolutional neural networks (CNN) are quickly becoming one of the most powerful tools for earth observation image data analysis [7], [8]. However, such models have never been applied yet in the context of SAR raw data compression, mainly due to the lack of significant correlation and self-similarity typically observed in the raw data domain, which complicates the task of pattern recognition.
Here, we investigate the potential of an AI-based methodology for defining a flexible approach for on-board performance-optimized raw data quantization in future SAR missions, where a locally variable bitrate is derived depending on a desired target performance in the focused SAR/InSAR data domain, without the need of a priori in formation on the acquired scene. This challenging task is accomplished through a deep learning-based method, which directly links input raw data to corresponding performance parameters computed in the focused SAR domain. We have approached the task of onboard bitrate estimation for SAR raw data as a deep, fully supervised regression task. In the specific, the number of quantization bits to be allocated for a given portion of the raw data is estimated by a DL architecture within a continuous range of possible values (i.e., between 2 and 6 bits/sample). The principle of the proposed method is shown in Fig. 1. Here, the input raw data is fed into the DL architecture which estimates a two-dimensional bitrate map (BRM), while a standard BAQ is then considered to compress the raw data by applying the estimated (variable) BRM. In the specific, azimuth/range-switched quantization is used to implement non-integer rates as in [3].

**DL Architecture Description**

The DL architecture that we have defined is presented in Fig. 2(a): it consists of a sequence of three convolutional layers (with 64, 128 and 256 3×3 kernels, respectively) with rectified linear unit (ReLU) activation function, interleaved by max pooling layers which halves the dimensions of the input features at each layer. Afterwards the feature maps are "flattened" and provided as input to a fully-connected dense layer with 128 units, followed by a final linear regression layer which returns a vector of M bitrate values (where M represents the number of optimization parameters considered during the training process). Therefore, at inference stage, one single BAQ bitrate value is derived and applied to blocks of 128×128 pixels within the input raw data. We chose the mean squared error (MSE) as loss function between the network output and the reference bitrate map, estimated from the corresponding focused SAR data. The considered hyperparameters (number of layers, number of kernels, size of the dense layer and size of the input patches) have been selected through empirical hyperparameter tuning, as a trade-off between achievable performance and onboard computational complexity. In the specific, an input raw data patch of size 128×128 samples (in range and azimuth dimensions, respectively) implies the storage in the onboard memory of 128 contiguous range lines, which is a feasible size with respect to currently availa-

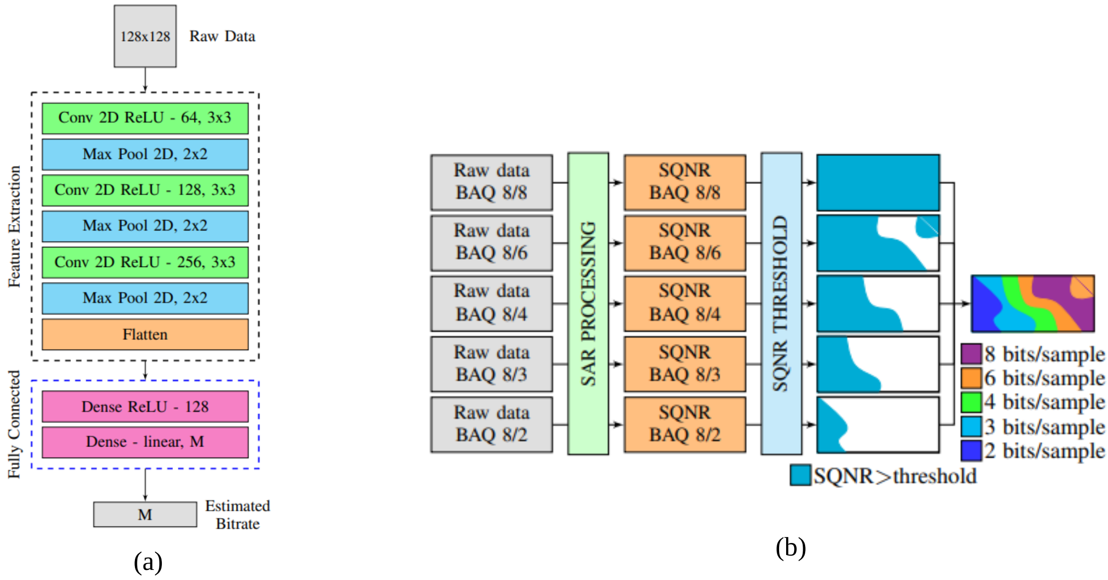



Fig. 2. (a) Block scheme of the proposed DL architecture. The initial feature extraction blocks consist in a sequence of two-dimensional convolutions with ReLU activation function and max pooling terminated by a flattening operation. The fully connected dense layer of 128 elements with ReLU activation is linked to the output regression element consisting of an M-elements dense layer with linear activation function, where M represents the number of target SAR optimization parameters. (b) Approach used to derive the reference BRMs for training the DL architecture based on thresholding for a given performance requirement. In this case, the SQNR is selected as performance parameter, but the same method can be applied to other metrics as well (e.g., phase error, coherence loss).

ble hardware components for spaceborne SAR [9]. At the same time, 128 range samples represent the standard range block size for the BAQ quantizer in current spaceborne SAR missions. Clearly, the number and size of the convolutional kernels and of the dense layers directly impact the required onboard processing and computational burden as well.

For the generation of a descriptive and consistent dataset to train, validate and test the proposed architecture, we have exploited TanDEM-X data acquired in bypass configuration, i.e., raw data are quantized with a uniform 8-bit Analog-to-Digital Converter (ADC) only. We have selected the acquisitions to feature a variety of land cover types including desert, ice, forest, urban areas and different topography conditions. The generation of the reference bitrate maps to be used during training and testing was based on the principle of PO-BAQ [4]. In particular, we re-quantized each acquisition on ground using different BAQ rates (i.e., 2, 3, 4 and 6 bits/sample), and then performed the complete SAR processing, allowing for the derivation of SAR and InSAR products for each different quantization rate. In order to achieve more granularity in the reference data, even if only integer (BAQ) bitrate values are available, we performed an interpolation on the obtained performance, such that we were able to define a fractional bitrate which satisfies the requirement, as it is presented in [4]. Afterwards, we derived a binary mask for each re-quantized raw data, by setting a threshold on the specific target performance parameter. An overall reference bitrate map is then obtained by selecting the minimum number of bits which satisfies a certain performance within the focused SAR data. This concept is depicted in Fig. 2(b) for the exemplary case of the signal-to-quantization noise ratio (SQNR) as target performance metric. The signal-to-quantization noise ratio (SQNR) describes how much the output signal has been corrupted by quantization noise. It is defined as the power ($\sigma^2$) ratio of the input $x$ to the quantization error $q = x - \hat{x}$ and, for a complex SAR image composed by $P$ pixels, it is calculated as

$$\mathrm{SQNR} = \frac{\sum_{p=1}^{P} |x_p|^2}{\sum_{p=1}^{P} |q_p|^2} = \frac{\sigma_x^2}{\sigma_q^2}. \tag{1}$$

The SQNR can be related to the total signal-to-noise ratio (SNR) as follows

$$\mathrm{SNR} = \frac{\sigma^0}{\sigma_n^2} = \frac{\sigma^0}{\sigma_t^2 + \sigma_q^2} \rightarrow \ \mathrm{SNR}^{-1} = \mathrm{STNR}^{-1} + \mathrm{SQNR}^{-1}, \tag{2}$$

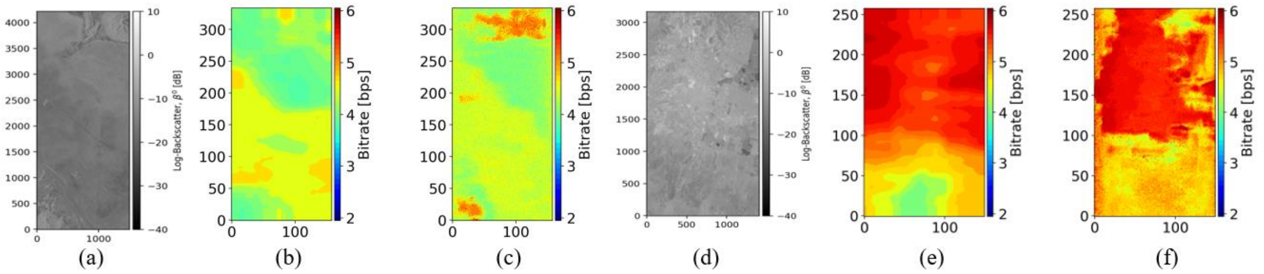



Fig. 3. Log-backscatter $\boldsymbol{\sigma^0}$ map of the (a) Uyuni (Bolivia) and (d) Mexico City (Mexico) areas selected for testing of the proposed method. (b) and (e) Corresponding bitrate maps for a target performance of SQNR=20 dB; (c) and (f) resulting inference (test, estimated bitrate map) results for the two areas.

Table 1. Mean ± standard deviation of SQNR calculated on the final SAR single-look complex product for four considered test scenes. The proposed method (AI-BAQ) is evaluated for different performance targets (SQNR = [10, 15, 20, 25] dB), and the resulting average bitrate is shown as well for each case. The performance of constant-rate BAQ at 2, 3 and 4 bps is reported for comparison (last three rows of the table).

| Method | Target | Greenland | Uyuni | Las Vegas | Mexico City |
|---|---|---|---|---|---|
| AI-BAQ | SQNR=10dB | 10.7±0.1@2.2bps | 10.2±0.5@2.2bps | 9.7±1.3@2.5bps | 9.6±0.9@2.7bps |
| | SQNR=15dB | 15.6±0.2@3.2bps | 15.3±0.6@3.1bps | 14.7±1.3@3.5bps | 14.5±0.9@3.7bps |
| | SQNR=20dB | 18.7±0.6@4.2bps | 20.5±0.5@4.4bps | 20.0±1.3@5.0bps | 19.7±1.0@5.1bps |
| | SQNR=25dB | 22.6±1.1@5.1bps | 25.0±0.6@5.4bps | 23.8±1.3@5.8bps | 24.0±1.1@5.8bps |
| BAQ@2bps | - | 9.3±0.2 | 9.5±0.2 | 7.7±1.3 | 6.6±1.4 |
| BAQ@3bps | - | 15.1±0.2 | 15.0±0.4 | 12.9±1.5 | 11.6±1.8 |
| BAQ@4bps | - | 18.7±0.4 | 19.8±0.7 | 17.8±1.6 | 16.5±1.8 |

being $\sigma^0$ the radar backscatter, $\sigma_t^2$ and $\sigma_n^2$ the thermal and total noise, respectively, and STNR the signal-to-thermal noise ratio. During the training phase, the input to our DL architecture consists of 128×128 samples patches of uncompressed raw data amplitude. In order to link this information to the corresponding reference bitrate value, the derived reference BRM is averaged within a window of the same size of the corresponding raw data patch (128×128 samples), centered around the patch center sample. In this way, a single reference bitrate value is associated to the entire input raw data patch. The achieved granularity (1 bitrate value per patch) does not cause a loss of information, as smooth spatial variability is observed in the original reference BRM [4]. In this work we optimize for specific values of SQNR, but it is worth noting that the SQNR is only one possible optimization parameter, the same process could also be performed for deriving the required bitrate maps based on other performance metrics (e.g., SAR interferometric coherence, total SNR and phase error). Overall, we have trained the network using a dataset of almost 11 million data patches, derived from 17 TanDEM-X bistatic SAR images, whose 80% (randomly selected) have been considered as training samples, while the remaining, independent 20% have been used as validation samples.

**Results**

As inference example, we consider a TanDEM-X acquisition over Uyuni (Bolivia) and an urban area of Mexico City (Mexico), whose log-backscatter maps $\boldsymbol{\sigma^0}$ are depicted in Fig. 3(a) and Fig. 3(d), respectively. They represent a homogeneous and a highly heterogeneous scene, respectively and, in particular, the latter is characterized by the presence of urban structures, lakes and high-relief topography. Fig. 3(b) and Fig. 3(d) depicts the corresponding reference BRMs, and Fig. 3(c) and Fig. 3(e) the estimated (test) BRMs for the two scenes. In this example, a target SQNR of 20 dB is considered, and it is possible to observe the high degree of adaptivity of the method: even though the performance requirement is the same for the two scenes, the architecture is able to assign the target rate in the correct range of values, which is considerably different between the two scenarios, due to the different characteristics in the backscatter distribution for each scene. In order to properly assess the effectiveness of the proposed method, we evaluated the performance on the final quantized SAR product. To do so, we have applied the estimated BRM for variable quantization of the uncompressed raw data, and carried out the complete SAR processing for each case. The results of this analysis are reported in Table 1 together with the state-of-the-art BAQ for 2, 3 and 4 bit/sample for comparison. These results highlight

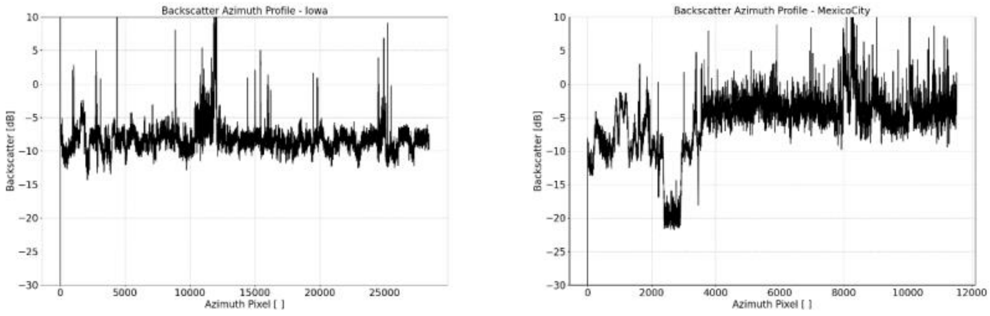
Table 2: Multi-channel SAR parameters for the three selected system.

| Parameter | ROSE-L-like | HRWS C-band | HRWS X-band |
|---|---|---|---|
| Carrier frequency, $f_c$ | 1.25 GHz | 5.04 GHz | 9.65 GHz |
| Satellite height, $h_s$ | 697 km | 697 km | 514 km |
| Antenna type | Planar array | | |
| Acquisition mode | Stripmap | | |
| Azimuth antenna length, $L_a$ | 11 m | 12.8 m | 5.04 m |
| Number of azimuth channels, $N$ | 5 | 8 | [4, 8] |
| Pulse repetition frequency, $\mathrm{PRF_{Tx}}$ (uniform sampling) | 1364 Hz | 1188 Hz | 3017 Hz |
| Target azimuth resolution, $\delta_a$ | [1.5, 3, 5, 10] m | | |
| Total processed bandwidth, PBW | [4510, 2255, 1353, 676] Hz | [4510, 2255, 1353, 676] Hz | [4691, 2346, 1407, 704] Hz |
| ADC Resolution | 8 bits | | |

the capability of the architecture to meet the desired performance requirement in terms of SQNR with respect to the considered optimization parameters (10, 15, 20 and 25 dB respectively). Moreover, in strong heterogeneous scenes (Las Vegas and Mexico City) BAQ performance degrades severely, as expected for these challenging scenarios [5] and, consequently, the bit rate values estimated by the AI-BAQ are higher in order to adaptively mitigate the quantization errors. For more homogeneous scenes (such as Greenland and Uyuni), on the other hand, the resulting bit rate is lower as quantization errors are less affecting in the final SAR performance. This feature verifies the strong adaptivity of the AI-BAQ method with respect to the local characteristics of the imaged scene.
As next step, we aim at implementing and demonstrating the proposed AI-BAQ method on a neuromorphic on-board computer (OBC), which will be carried out in the frame of the DLR internal project ADMIRE (“ADvanced and MIniaturized Radar-Enabling technologies”).

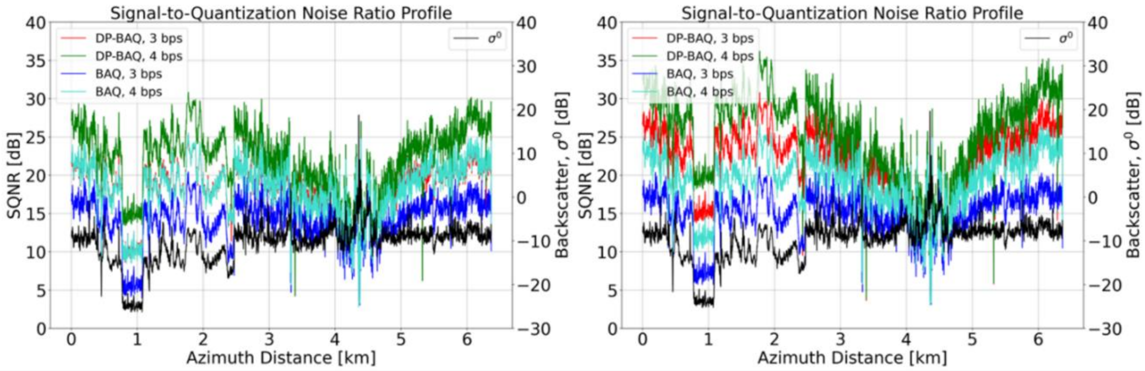
## EFFICIENT DATA VOLUME REDUCTION FOR MULTICHANNEL SAR

Multi-channel SAR allows for overcoming the inherent trade-off of conventional (single-channel) SAR systems in terms of achievable swath width and azimuth resolutions. Indeed, by exploiting multiple receiving apertures which are mutually displaced in the along-track dimension, the coherent combination of the individual received signals allows for adequate suppression of the ambiguous parts of the Doppler spectra and, in this way, high-resolution wide-swath imaging is achieved [10], [11]. The drawback for such an improvement of swath coverage and resolution is represented by a significantly larger data volume to be acquired and transmitted to the ground. In this work, three multichannel SAR system examples are investigated, and the corresponding system parameters are summarized in Table 2: in particular, different radar frequencies – L, C, and X band – are considered, and the parameters are realistic for currently investigated multichannel SAR missions, such as the ROSE-L and a Sentinel-NG-like system. To investigate potentials and limitations of data volume reduction for multichannel SAR, we have analyzed the multichannel SAR raw signal characteristics, such as the autocorrelation and the Doppler power spectrum by means of simulations and generation of synthetic data as well as real TanDEM-X backscatter profiles, to identify relevant trade-offs of SAR system parameters in the context of data volume reduction: we have considered two simulated azimuth profiles: a homogeneous backscattter profile, where the power level of the complex signal is kept constant, and a profile with a “jump” of 20 dB (i.e. varying from -10 to +10 dB along azimuth, these profiles are not depicted due to space constraints). Furthermore, Fig. 4 shows two backscatter profiles obtained from TanDEM-X data: Fig. 4(a) represents an azimuth profile taken from an agricultural (rather homogeneous) site in Iowa (USA), while Fig. 4(b) shows a backscatter profile along azimuth over Mexico City, a quite heterogeneous area and characterized by urban settlements and rugged topography. To extract both profiles in Fig. 4, a one-pixel, single-look azimuth line from the SAR image has been considered. The variety of the backscatter profiles and statistics considered in this analysis is exploited to gain more confidence and representativeness with respect to the obtained results and performance.




(a) (b)

Fig. 4. Backscatter profiles taken from real TanDEM-X acquisitions used for the multi-channel SAR raw data generation: azimuth backscatter profile from (a) an agricultural area in Iowa (USA) and (b) the area of Mexico City.




(a) (b)

Fig. 5. SQNR profiles for different quantization schemes (BAQ and DP-BAQ as in [12]) and bitrate (3 and 4 bps), depicted with different colors, for a backscatter profile over the urban area of Mexico City (shown in black). The X-band HRWS multichannel system is considered for (a) $N = 4$ and (b) $N = 8$ channels.

The simulated profiles and the ones shown in Fig. 4 are used to generate multi-channel SAR raw data along azimuth, and from these different parameters and quantities are analyzed for three multi-channel SAR system examples. In particular, we have considered the impact of the antenna pattern shape (azimuth length, carrier frequency), the number of azimuth channels $N$, the PRF and more specifically the oversampling factor $o_f$ = PRF/PBW, being PBW the processed Doppler bandwidth. As an example, based on the oversampling and the autocorrelation properties exhibited by the HRWS X-band system (right column in Table 2), we present the potential of linear predictive coding (LPC) for efficient data volume reduction. For this, we applied the Dynamic Predictive (DP)-BAQ proposed by the authors in [12] in the context of staggered SAR systems: Fig. 5 illustrates the SQNR for the case of (a) $N = 4$ and (b) $N = 8$ channels (corresponding to a $o_f = 2.6$ and $o_f = 5.2$ for the 1.5 m resolution case, respectively), evaluated for a backscatter azimuth profile of a TanDEM-X scene over the urban area of Mexico City (in black, right y-axis). The resulting SQNR profiles are derived for the BAQ and the proposed DP-BAQ [12] (depicted with different colors), and a consistent data volume reduction with respect to the 4-bit BAQ case of about 25% up to more than 50%, for the case in Fig. 5(a) and Fig. 5(b), respectively, is achieved. We also considered the transform-coding-based data compression method proposed in [13], referred to as multichannel (MC)-BAQ, which is based on a joint transformation in the Doppler domain of the multichannel block and adaptive bitrate allocation. Fig. 6 shows the data volume reduction achievable by the HRWS C-band system, for the different considered backscatter profiles (depicted with different colors) and azimuth resolutions, corresponding to processed bandwidth ranging from about 700 Hz to 4600 Hz, which results in a data reduction (w.r.t. the 4-bit BAQ case) up to 40%, hence verifying the suitability of the proposed method for data volume reduction in multi-channel SAR.

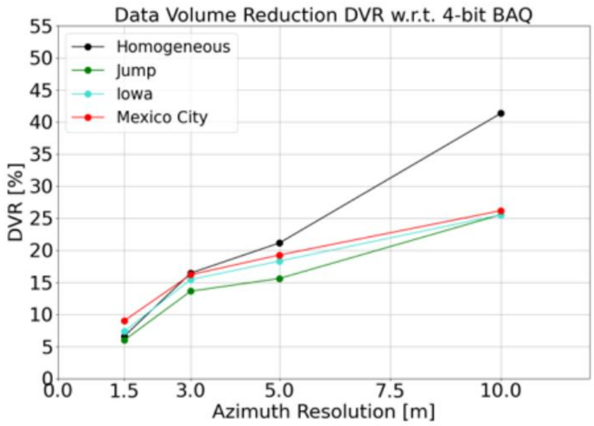


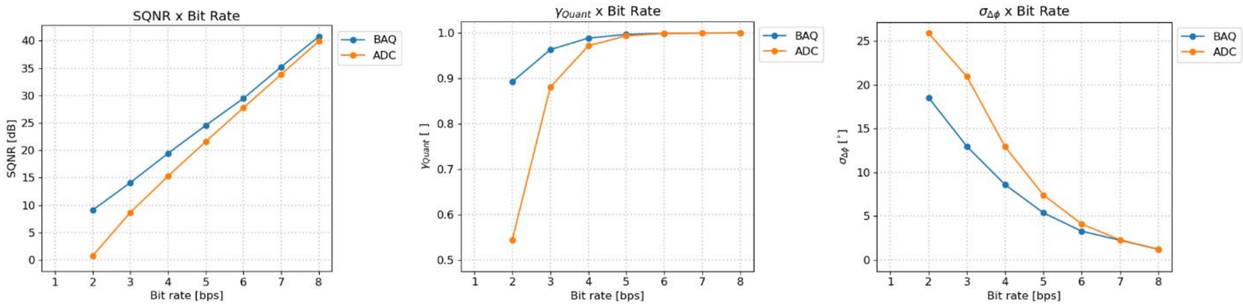

Fig. 6. Data volume reduction (DVR) in % with respect to the 4-bit BAQ case, for the HRWS C-band system, as function of the azimuth resolution (i.e. Doppler bandwidth) for the considered azimuth profiles, with different colors.

## CCSDS ACTIVITIES

In the frame of the Consultative Committee for Space Data Systems (CCSDS) activities, DLR currently support the Data Compression Working Group with the main objective of standardizing data compression methods for SAR systems. After having contributed, during a first period of activities, to the revision and redrafting of the documentation for the standardization of the Flexible Dynamic FDBAQ, together with the Working Group it was then reconsidered to define a more general and well-established compression scheme for SAR, leaving to the user the opportunity of potentially setting specific requirements on performance and data rate (as it is implemented by the FDBAQ). As first analysis, we have started to carry out simulations of complex SAR raw data, modeled as realization of circular Gaussian random variables, quantized with both BAQ and ADC to verify the fidelity of both approaches. The obtained results are shown in Fig. 7, which depicts the SQNR (Fig. 7(a)), the correlation factor $\gamma_{Quant}$ (Fig. 7(b)) and the standard deviation of the phase error due to quantization $\sigma_{\Delta\varphi}$ (Fig. 7(b)) as function of the bit rate, and highlight the superiority of the adaptive quantization (BAQ, in blue) with respect to uniform, non-adaptive digitization (ADC, in orange). The possibility of standardizing the BAQ compression scheme and more in general the next steps of the activities will be discussed during the CCSDS Fall Meeting in November 2024.

## CONCLUSIONS AND OUTLOOK

In this paper we first investigated the potential of Deep Learning for deriving an on-board performance-optimized bitrate allocation for SAR systems. For this, we generated a proper training dataset by commanding experimental uncompressed bistatic TanDEM-X acquisitions to derive reference bitrate maps for the DL architecture. The obtained performance and results confirm the effectiveness of the proposed method. Furthermore, we analyzed further opportunities for data volume reduction in multichannel SAR. For such systems, efficient data compression strategies can be proposed, which aim at exploiting the existing correlation between subsequent azimuth samples. We assessed the statistical properties of the multichannel raw signal have been considered and, for performance assessment, we considered three multichannel SAR system architectures. Based on these, we simulated multi-channel raw data using synthetic data as well as backscatter profiles from real SAR TanDEM-X. The obtained results and performance assessment are promising, highlighting the trade-off, potential and limitations of the proposed methods for data volume reduction in multichannel SAR. Finally, we provided a brief overview of the contributions provided by the Microwaves and Radar Institute of DLR in the Data Compression Working Group of the CCSDS. As next steps, we will conduct an end-to-end performance evaluation on SAR/InSAR performance (i.e. not limited to quantization degradation only), together with an assessment of the non-linear and signal-dependent impact of SAR compression on different quality measures (e.g. detection, phase). Furthermore, we will implement and demonstrate the feasibility of the proposed AI-BAQ method on a neuromorphic on-board computer in the frame of the DLR internal ADMIRE ("ADvanced and MIniaturized Radar-Enabling technologies") project. Finally, we plan to investigate the potential of the proposed methods in the context of multi-static SAR configurations.




(a) (b) (c)

Fig. 7. (a) SQNR, (b) correlation factor $\boldsymbol{\gamma_{Quant}}$ and (c) standard deviation of the phase error $\boldsymbol{\sigma_{\Delta\varphi}}$ obtained using a uniform ADC (in orange) and an adaptive BAQ (in blue).


## ACKNOWLEDGEMENTS

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