AI for Optimized Raw Data Quantization in SAR Systems

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Abstract—**Next-generation SAR systems will feature high-resolution wide-swath acquisitions, resulting in a significant increase of the onboard data volume to be acquired by the system. This causes severe constraints in terms of onboard memory requirements and downlink capacity. In this scenario, an efficient onboard quantization of the raw data is of utmost importance, representing a trade-off between achievable product quality and consequent on-board data volume. In this paper, we investigate the use of artificial intelligence (AI), and in particular of deep learning (DL), for flexible and on-board SAR raw data quantization. The aim is to derive an optimized and adaptive data rate allocation given a set of desired performance metrics and requirements in the resulting focused SAR image without relying on a priori information on the acquired scene. The obtained bitrate maps (BRMs) can then be dynamically used as input to a state-of-the-art BAQ quantizer to perform the on-board raw data digitization. The proposed method aims at directly linking the characteristics of the SAR raw data to performance parameters computed in the focused SAR domain, without the necessity for performing on-board focusing. For optimizing the proposed DL model architecture, we consider multiple target performance parameters such as the Signal-to-Quantization Noise Ratio (SQNR), the InSAR coherence loss or the interferometric phase error, extending the capabilities of the architecture and, ideally, providing multiple bitrate estimations for a single input scene at a time, depending on the specific application requirement. The proposed method allows for an efficient joint optimization and reduction of the data rate and of the resulting performance setting a new paradigm for data reduction in future SAR systems.**

I. Introduction

Synthetic Aperture Radar (SAR) systems have revolutionized remote sensing, providing high-resolution images regardless of weather conditions or daylight illumination [1]. Next generation SAR systems will bring a huge improvement in performance by means of novel acquisition modes, large bandwidths and digital beamforming (DBF) techniques [2]–[6]. These enhanced capabilities will inevitably cause the generation of larger amounts of onboard data, which, in turn, poses stringent requirements for onboard memory resources and downlink capacity.

In this context, an efficient quantization of the SAR raw data is of primary importance: on the one hand it defines the amount of onboard memory to be allocated and, on the other hand, it directly affects the quality of the resulting SAR products. These two aspects must be thoroughly considered due to the limited onboard resources and acquisition capacity of the system and, at the same time, to achieve the specified product requirements and quality.

For present SAR missions, SAR raw data quantization is usually carried out by means of the Block-Adaptive Quantization (BAQ) [7]. 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) [8], which may even be combined with the implementation of non-integer data rates [9]. However, the FDBAQ performs a bitrate optimization based on the SAR raw data statistics only, while it does not take into account the actual performance degradation in the final SAR products.

The Performance-Optimized BAQ (PO-BAQ) [10] extends the concept of BAQ and represents the first attempt for an optimization of the resource allocation depending on 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 amount 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 [11], 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 [10]. 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 [12]. In particular, convolutional neural networks (CNN) are quickly becoming one of the most powerful tools for earth observation image data analysis [13], [14]. However, such models have never been applied yet in the context of SAR raw data digitization and 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.

In this contribution 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-

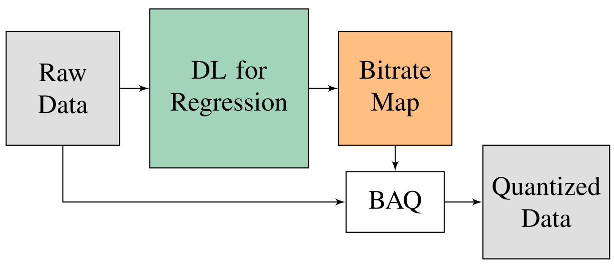


Fig. 1. Flow chart of the proposed method for a dynamic bitrate allocation using DL: the raw data matrix is provided to the trained DL model which predicts the required two-dimensional bitrate map (BRM), needed to achieve the desired performance. An adaptive quantizer (i.e., BAQ) performs the raw data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

formation on the acquired scene. This challenging task is accomplished though a deep learning-based method, which directly links input raw data to corresponding performance parameters computed in the focused SAR domain.

The paper is structured as follows: the description of the proposed method, named AI-BAQ, which includes the model architecture and training strategy, is presented in Section II. In Section III results are shown including the validation on the final SAR product. Finally, conclusions and outlook are provided in Section IV.

II. Deep Learning for SAR Raw Data Quantization

In this contribution, 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 [9].

A. DL Architecture Description

The DL architecture that we have defined is presented in Fig. 2: 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. As loss function we utilized the mean squared error (MSE) between the network output and the reference bitrate map, estimated from the

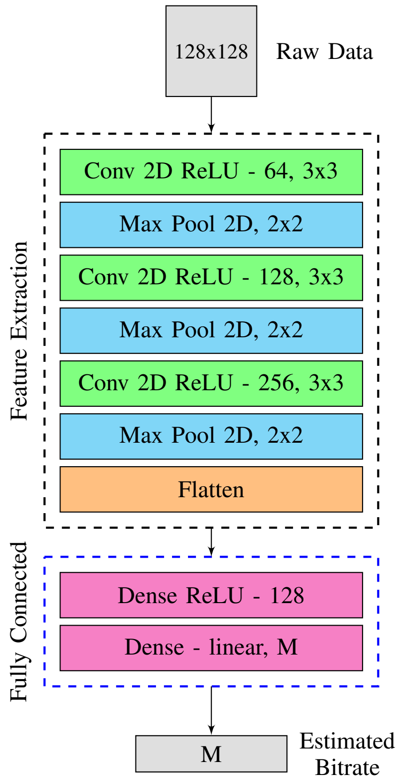


Fig. 2. Block scheme of the proposed DL architecture. The initial feature extraction blocks consist in a sequence of two-dimensional convolutions with ReLU activation function and max pooling terminated by a flattening operation. The fully connected dense layer of 128 elements with ReLU activation is 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.

corresponding focused SAR data, as presented in Section II-B. 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 available hardware components for spaceborne SAR [15]. 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 impacts the required onboard processing and computational burden as well.

B. Dataset Generation and Training Phase

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,

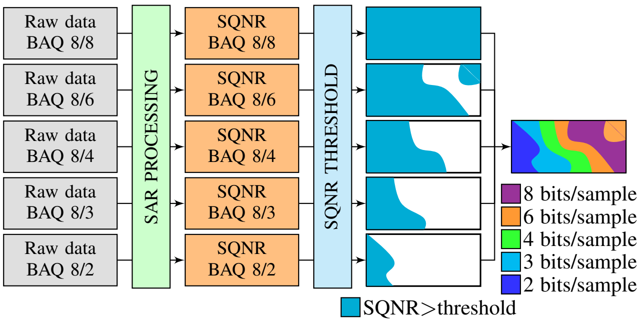


Fig. 3. Approach used to derive the reference BRMs for training the DL architecture based on thresholding for a given performance requirement. In this case, the SQNR is selected as performance parameter, but the same method can be applied to other metrics as well (e.g., phase error, coherence loss).

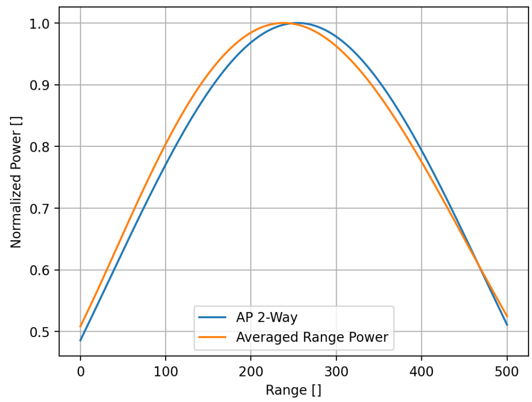


Fig. 4. Range beam pattern used for the acquisition (blue curve) and raw data power (averaged along the azimuth dimension) over a uniform scene (Greenland). The strong agreement between the two curves suggests that a coarse range pattern compensation is necessary to provide unbiased raw data input to the proposed DL architecture.

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 [10]. 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 [10]. 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 derived by selecting the minimum number of bits which satisfies a certain performance within the focused SAR data. This concept is depicted in Fig. 3 for the exemplary case of the signal-to-quantization noise ratio (SQNR) as target performance metric, which is defined as

$$\mathrm{SQNR} = \frac{\sigma_s^2}{\sigma_q^2}, \quad \text{with} \quad q = s - s_q. \tag{1}$$

In the above equation s and s_q represent the reference (non-quantized) signal and the quantized one, respectively.

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 [10].

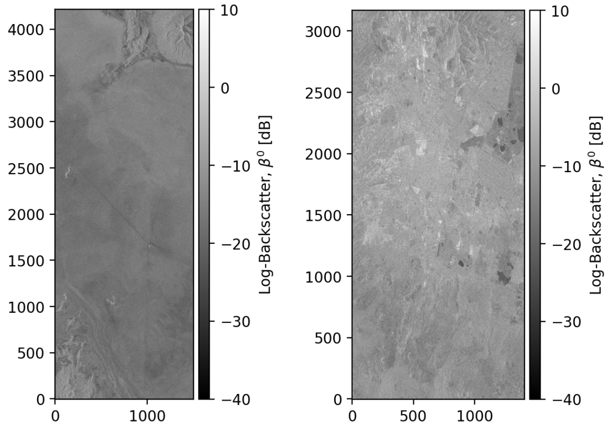
One should be aware that the input data (i.e., raw data) does not feature any kind of range antenna pattern compensation, while the output (i.e., bitrate map derived from focused SAR domain) actually includes that. This can lead to inconsistent bitrate estimations as the raw data intensity strongly varies along the range direction depending on the position within the illuminated swath. Fig. 4 illustrate the described effect: the normalized raw data range power derived over a uniform scene over Greenland and the respective range beam pattern considered in the acquisition are depicted. As we are assuming not to carry out any SAR processing step implemented on-board, we cannot afford to precisely compensate for the range pattern in the range-compressed domain, but, as Fig. 4 suggests, a similar compensation in the raw data domain can be still meaningful in order to remove the effect of the beam and to avoid introducing biases in the DL model. This is done by dividing each range line by the considered range beam pattern. It is worth noting that this coarse compensation is performed only for the bitrate estimation, hence not impacting the actual raw data before quantization.

In this contribution 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, Signal-to-noise ratio 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.

III. 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 are depicted in Fig. 5. They represent a homogeneous and a highly heterogeneous scene, respectively. In particular, the latter is characterized by the presence of urban structures, lakes and high-relief topography. Fig. 6 depicts the reference BRMs (Fig. 6 left



(a) (b)

Fig. 5. Log-backscatter β^0 map of the (a) Uyuni (Bolivia) and (b) Mexico City (Mexico) areas selected for testing the proposed AI-based bitrate allocation method.

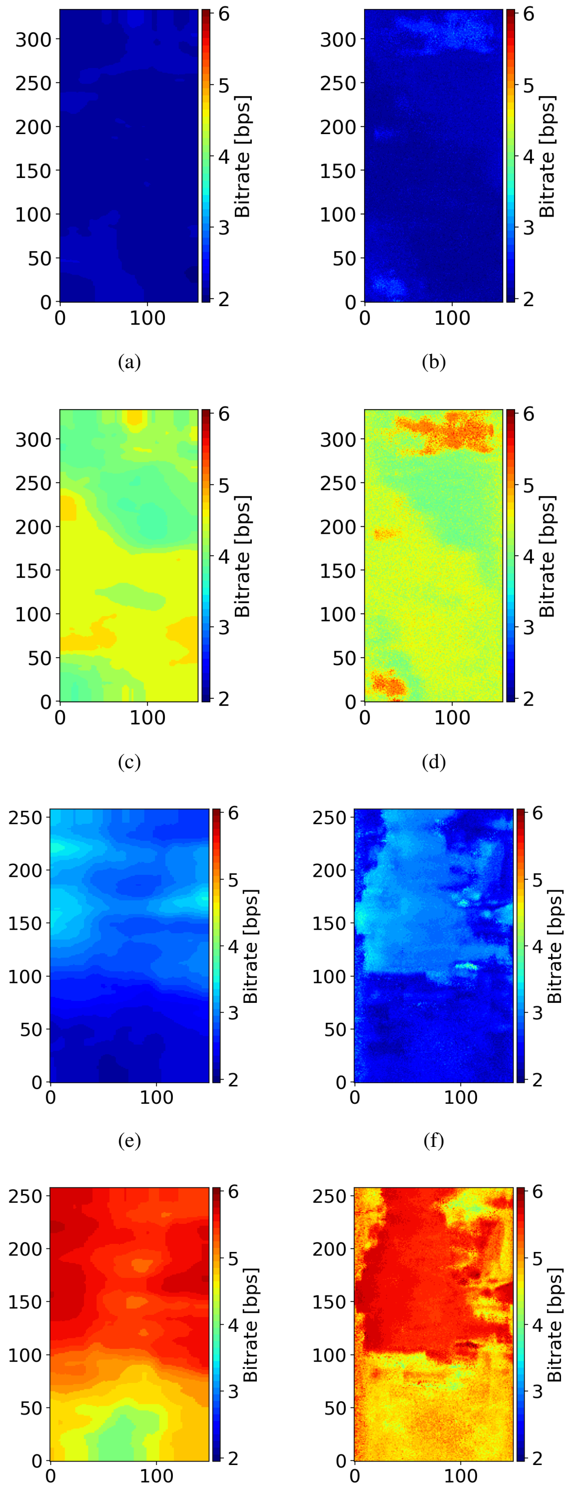
TABLE I
BITRATE ESTIMATION ERROR FOR THE INVESTIGATED CASES (MEAN $\pm$ STANDARD DEVIATION)

Performance	Greenland	Uyuni	Las Vegas	Mexico City
SQNR=10 dB	0.13±0.10	0.06±0.14	0.01±0.32	-0.07±0.29
SQNR=15 dB	0.18±0.13	0.06±0.18	0.04±0.35	-0.06±0.31
SQNR=20 dB	-0.19±0.19	0.06±0.18	0.02±0.35	-0.09±0.32
SQNR=25 dB	-0.11±0.28	-0.01±0.17	-0.15±0.39	-0.16±0.29

column), and the estimated BRMs (Fig. 6 right column) for the two scenes (Uyuni on the upper two rows and Mexico City for the lower two). In this example, a target SQNR of 10 dB (Fig. 6(a)-(b) and Fig. 6(e)-(f)) and 20 dB (Fig. 6(c)-(d) and Fig. 6(g)-(h)) are considered. As an example, by comparing the estimation for the 20 dB SQNR case for the two scenes, 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 and grade of heterogeneity of each scene.

In Table I we report the complete inference results in terms of average bitrate error and its standard deviation with respect the reference. One can note that the achieved estimation errors are almost unbiased (the average error is typically a small fraction of 1 bit/sample) and the dispersion (standard deviation) is well confined between ± 0.5 bit/sample for all investigated cases.

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 II together with the state-of-the-art BAQ for 2, 3 and 4 bit/sample for comparison. These results highlight the capability of the architecture to meet the desired performance requirement in terms of



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 6. Inference results over the area of Uyuni (a)-(d) and Mexico City (e)-(h) for the target cases of SQNR=10 dB and SQNR=20 dB. Reference bitrate maps are reported on the left column, while estimated (test) bitrate map are reported on the right column. Figures (a)-(b) and (e)-(f) refer to the SQNR=10 dB case, while Figures (c)-(d) and (g)-(h) to the SQNR=20 dB. It is possible to see that the estimation results are consistent, and able to follow the range of values of the reference cases.

TABLE II
SAR PERFORMANCE (IN TERMS OF MEAN AND STANDARD DEVIATION OF SQNR) ON THE FINAL SAR PRODUCTS ON THE FOUR TEST ACQUISITIONS. THE PROPOSED METHOD (AI-BAQ) WITH FOUR DIFFERENT PERFORMANCE TARGETS (AND ITS RESULTING AVERAGE BITRATE) AND THE STATE-OF-THE-ART BAQ AT 2, 3 AND 4 BPS ARE REPORTED BELOW.

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

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 in this challenging scenarios [11]. In these cases, the resulting number of bits for the AI-BAQ are higher in order to mitigate the quantization errors. For heterogeneous scenes, instead, the resulting rate is much lower as quantization errors are less impacting in the final SAR performance. This aspect is crucial and shows the strong adaptivity of the method on the local characteristics of the imaged scene.

IV. Conclusions and Outlook

In this paper we investigate a novel approach for an adaptive, performance-optimized bitrate allocation for SAR and InSAR systems by means of a Deep Learning-based regression architecture. Important advantages of the proposed method rely in the fact that no a priori information is required by the system for its implementation and that different bitrate allocations can be simultaneously derived depending on the considered performance parameter and target requirement.

We have presented relevant aspects and details of the developed DL network as well as the definition of the training, validation and testing datasets and strategies, together with an assessment of the estimation performance on independent test acquisitions. The achieved results are extremely promising and show that an accurate bitrate estimation can be adaptively generated by the proposed architecture, which is then consistently confirmed when the performance parameters are evaluated on the final SAR product. The comparison with the state-of-the-art BAQ scheme highlights the flexibility of the method to meet the desired performance on different scenes. As outlook to this work, additional optimization of the architecture is foreseen in order to further improve the performance, as well as the number of optimization parameters which can be handled by the architecture. The exploitation of a larger dataset will allow for the training of a more robust model and in view of a global-scale assessment of the data rate for future SAR missions.

Acknowledgement

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References

[1] Gerhard Krieger, Alberto Moreira, Hauke Fiedler, Irena Hajnsek, Marian Werner, Marwan Younis, and Manfred Zink, "TanDEM-X: A Satellite Formation for High-Resolution SAR Interferometry," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 11, pp. 3317–3341, 2007.

[2] Paul Rosen, Scott Hensley, Scott Shaffer, W Edelstein, Yunjin Kim, R Kumar, Tapan Misra, Rakesh Bhan, and R Sagi, "The NASA-ISRO SAR (NISAR) mission dual-band radar instrument preliminary design," in *2017 IEEE international geoscience and remote sensing symposium (IGARSS)*. IEEE, 2017, pp. 3832–3835.

[3] Kent Kellogg, Pamela Hoffman, Shaun Standley, Scott Shaffer, Paul Rosen, Wendy Edelstein, Charles Dunn, Charles Baker, Phillip Barela, Yuhsyen Shen, et al., "Nasa-isro synthetic aperture radar (nisar) mission," in *2020 IEEE Aerospace Conference*. IEEE, 2020, pp. 1–21.

[4] Nazzareno Pierdicca, Malcolm Davidson, Marco Chini, Wolfgang Dierking, Samuel Djavidnia, Joerg Haarpaintner, Guillaume Hajduch, Gaia V Laurin, Marco Lavalle, Carlos López-Martínez, et al., "The copernicus l-band sar mission rose-l (radar observing system for europe)(conference presentation)," in *Active and Passive Microwave Remote Sensing for Environmental Monitoring III*. SPIE, 2019, vol. 11154, p. 111540E.

[5] Dirk Geudtner, Michel Tossaint, Malcolm Davidson, and Ramón Torres, "Copernicus sentinel-1 next generation mission," in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*. IEEE, 2021, pp. 874–876.

[6] Mariantonietta Zonno, Jalal Matar, Felipe Queiroz de Almeida, Marwan Younis, Jens Reimann, Marc Rodriguez-Cassola, Gerhard Krieger, Andrea Perrera, and Michel Tossaint, "Sentinel-1 Next Generation: main mission and instrument performance of the phase 0," in *EUSAR 2021; 13th European Conference on Synthetic Aperture Radar*. VDE, 2021, pp. 1–5.

[7] Ronald Kwok and William TK Johnson, "Block adaptive quantization of Magellan SAR data," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 27, no. 4, pp. 375–383, 1989.

[8] Paul Snoeij, Evert Attema, Andrea Monti Guarnieri, and Fabio Rocca, "FDBAQ a novel encoding scheme for Sentinel-1," in *2009 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 2009, vol. 1, pp. I–44.

[9] Michele. Martone, Benjamin Bräutigam, and Gerhard Krieger, "Azimuth-switched quantization for SAR systems and performance analysis on TanDEM-X data," *IEEE Geoscience and Remote Sensing Letters*, vol. 11, no. 1, pp. 181–185, 2014.

[10] Michele Martone, Nicola Gollin, Paola Rizzoli, and Gerhard Krieger, "Performance-optimized quantization for SAR and InSAR applications," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–22, 2022.

[11] Michele Martone, Benjamin Bräutigam, and Gerhard Krieger, "Quantization effects in TanDEM-X data," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 2, pp. 583–597, 2015.

[12] Xiao Xiang Zhu, Devis Tuia, Lichao Mou, Gui-Song Xia, Liangpei Zhang, Feng Xu, and Friedrich Fraundorfer, “Deep learning in remote sensing: A comprehensive review and list of resources,” *IEEE Geoscience and Remote Sensing Magazine*, vol. 5, no. 4, pp. 8–36, 2017.
[13] Xiao Xiang Zhu, Sina Montazeri, Mohsin Ali, Yuansheng Hua, Yuanyuan Wang, Lichao Mou, Yilei Shi, Feng Xu, and Richard Bamler, “Deep learning meets sar: Concepts, models, pitfalls, and perspectives,” *IEEE Geoscience and Remote Sensing Magazine*, vol. 9, no. 4, pp. 143–172, 2021.
[14] Nicola Gollin, Michele Martone, Gerhard Krieger, and Paola Rizzoli, “AI-Based Performance-Optimized Quantization for Future SAR Systems,” in *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 2023, pp. 1771–1774.
[15] Geng Yang, Jie Lei, Weiying Xie, Zhenman Fang, Yunsong Li, Jiaxuan Wang, and Xin Zhang, “Algorithm/hardware codesign for real-time on-satellite CNN-based ship detection in SAR imagery,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–18, 2022.