Complex-Valued Autoencoder-Based Neural Data Compression for SAR Raw Data

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***Abstract*—Recent advances in Synthetic Aperture Radar (SAR) sensors and innovative advanced imagery techniques have enabled SAR systems to acquire very high-resolution images with wide swaths, large bandwidth and in multiple polarization channels. The improvements of the SAR system capabilities also imply a significant increase in SAR data acquisition rates, such that efficient and effective compression methods become necessary. The compression of SAR raw data plays a crucial role in addressing the challenges posed by downlink and memory limitations onboard the SAR satellites and directly affects the quality of the generated SAR image. Neural data compression techniques using deep models have attracted many interests for natural image compression tasks and demonstrated promising results. In this study, neural data compression is extended into the complex domain to develop a Complex-Valued (CV) autoencoder-based data compression for SAR raw data. To this end, the basic fundamentals of data compression and Rate-Distortion (RD) theory are reviewed, well known data compression methods, Block Adaptive Quantization (BAQ) and JPEG2000 methods, are implemented and tested for SAR raw data compression, and a neural data compression based on CV autoencoders is developed for SAR raw data. Furthermore, since the available Sentinel-1 SAR raw products are already compressed with Flexible Dynamic BAQ (FDBAQ), an adaptation procedure applied to the decoded SAR raw data to generate SAR raw data with quasi-uniform quantization that resemble the statistics of the uncompressed SAR raw data onboard the satellites.**

***Index Terms*—Data compression, neural data compression, rate-distortion theory, SAR raw data compression.**

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I. Introduction

NEXT generation SAR systems will offer an improved performance, using large bandwidths, digital beam forming techniques, and multiple acquisition channels [1], [2], [3]. These new radar systems are designed to overcome limitations of traditional SAR imaging sensors, enabling wider coverage and better resolution, and are being widely explored by space agencies and related industries. Such significant developments in terms of system capabilities lead to large volumes of data to be acquired in a shorter time interval, which, in turn, implies harder requirements for the onboard memory and downlink capacity of the system [4]. Consequently, the proper quantization and compression of SAR raw data is of utmost importance, as it defines, on the one hand, the amount of onboard data and, on the other hand, it directly affects the quality of the generated SAR products. These two aspects must be traded off due to the constrained acquisition capacity and onboard resources of the SAR system.

Data compression techniques are employed to reduce the size of the acquired SAR raw data without sacrificing critical information. By compressing data, the required downlink bandwidth is significantly reduced, enabling efficient transmission of SAR data from the satellite to the ground station. Moreover, data compression is essential for onboard memory management. SAR satellites have limited onboard storage capacity, and efficient data compression algorithms allow for storing larger amounts of data within the available memory. This enables longer data acquisition periods and increased mission flexibility, as SAR systems can acquire and store more data before the need for data offloading. Effective data compression techniques are essential for maximizing the utility of SAR systems.

However, conventional compression methods face significant challenges when applied to SAR data, largely due to its unique characteristics. One fundamental issue is that SAR data exist in the complex domain, while most traditional compression algorithms are designed for real-valued signals. Additionally, preserving the physical model underlying SAR data during compression is essential, which is not typically considered by conventional methods. The phase component of SAR data is particularly critical for applications such as focusing pipelines and Interferometric SAR (InSAR). Furthermore, SAR raw data exhibit low correlation, which inherently limits the efficiency of traditional data compression techniques.

These challenges combined with the other peculiarities of SAR data - such as its large dynamic range, inherent speckle effect, and the spatial correlation - necessitate the development of novel data compression methods for compressing SAR raw data, considering its unique characteristics. The particular statistics of the received signal should be considered while designing an effective data compression technique for SAR data. These constraints restrict the applicability and efficiency of the conventional image compression techniques for SAR raw data compression.

Block Adaptive Quantization (BAQ) is a widely used data compression technique for SAR raw data compression onboard the satellites, due to its efficiency and simplicity for coding and decoding [4]. BAQ divides the data into fixed-size blocks and applies adaptive quantization to each block based on its statistical characteristics, such as variance. This adaptability ensures that the compression remains efficient across regions with varying signal dynamics. BAQ is particularly effective for SAR data due to its ability to handle the large dynamic range and speckle characteristics inherent in radar signals [4]. Due to its wide usage in SAR systems, BAQ is used as one of the benchmark methods for comparison in this study.

Additionally, JPEG2000 is a popular image compression standard that employs wavelet-based compression and relies on discrete wavelet transform (DWT) to capture both spatial and frequency domain features of the image [5]. Previous studies [6] have shown that applying a lowpass filter on SAR raw data can reveal correlations in the data, which can be exploited for data compression. Experiments in [6] demonstrated that, despite its limitations in handling CV data, the wavelet filters used in JPEG2000 are effective for SAR raw data compression, when applied separately to the real and imaginary components. Due to its versatility and efficiency, JPEG2000 is employed as a benchmark method for comparison in this study.

Several studies have applied different data compression methods for SAR data compression, but mostly only for amplitude of the SAR images. For instance, optical compression standard methods such as JPEG2000 and Set Partitioning in Hierarchical Trees (SPIHT), wavelet transform-based methods [6], [7], [8], [9], [10], as well as machine learning and dictionary learning-based methods such as Entropy-Constrained Dictionary Learning Algorithm (ECDLA) [11], [12] have been tested for detected SAR image compression.

On the other hand, deep learning techniques have achieved remarkable results in many different fields and are gradually attracting interest for visual data compression [13], [14]. In this context, autoencoders are widely used for lossy image compression, mostly based on transforming the data into the latent space for quantization and reducing the bitrate of the image data, including detected SAR images [13], [15], [16].

Bearing in mind the huge potential and proficiency of the CV deep architecture for various SAR applications [17], [18], [19], this study inspects SAR raw data compression with CV deep architectures. The developed CV neural data compression method is tested for Sentinel-1 SAR raw data compression and the performance is compared with the well-known and standard SAR raw data compression methods, BAQ [4], and JPEG2000 data compression standards [6], in terms of quantitative and qualitative metrics, performance gain and generalizability.

Due to the unavailability of the uncompressed Sentinel-1 SAR raw data, the adaptation method, proposed in [20] to add random uniform quantization noise to the FDBAQ-compressed raw data, is utilized to generate quasi-uniformly quantized SAR raw data with similar statistics to the uncompressed SAR raw data onboard the satellite.

The main contributions of this study are:

- A fully complex-valued deep architecture is proposed for SAR raw data compression based on the rate-distortion theory. To the best of our knowledge, it is the first completely CV neural data compression architecture applied for SAR raw data compression.
- Capability of the proposed method for learning the underlying physical model of SAR raw data and preserving it during the data compression is tested.
- Comprehensive analyses demonstrated the efficiency and generalizability of the proposed method against standard and widely used data compression methods.

II. Methodology

In this section the dataset and the necessary preprocessing steps are explained. A brief introduction to BAQ and JPEG2000 data compression standards is given and the developed CV deep data compression architecture based on the rate-distortion theory and CV deep networks is explained.

A. Dataset and Preprocessing

Sentinel-1, part of the Copernicus programme, is a renowned SAR mission that offers free SAR data at various processing levels. Sentinel-1 SAR data have been instrumental in the development of numerous SAR applications [21], [22], [23], [24], [25]. In this study, three Sentinel-1 scenes acquired over Chicago and Houston in the United States, and Sao Paulo in Brazil, in StripMap (SM) mode with HH polarization, are used for training the deep learning model. Later, a subset of a separate Sentinel-1 scene acquired over Cape Verde, covering Sao Filipe constructed area, airport, surrounding bare soil and vegetation covers and the ocean, is used for testing the data compression methods. The test scene is selected to cover diverse land cover types, hence different backscattering mechanisms in the resulting SAR data.

However, the available Sentinel-1 SAR raw data (i.e., L0 product), which presently are the most popular, are already lossy compressed with FDBAQ [26] method. As a result, the decoded Sentinel-1 raw data have non-uniform quantization and do not have the same statistics as the uncompressed SAR raw data onboard the satellites. The adaptation of Sentinel-1 raw data introduced in [20] is used in this study to resemble the statistics of the uncompressed Sentinel-1 raw data, before the experiments. In this way we change the statistics of the compressed data such that we simulate the proper conditions for the evaluation of data compression algorithms, but this is not a return/inversion to the raw data obtained after the ADC. In this adaptation procedure, a random uniform noise with a suitable amplitude is added to the decoded SAR raw data to fill in the gaps between the quantization levels and represent the data in quasi-uniformly quantized samples [20]. The adaptation procedure provides a better approximation of the data compression methods behavior for real-world scenarios and ensures the applicability of the developed methods for SAR raw data compression onboard the satellites.

Furthermore, to evaluate the generalizability of the network when it is trained on one sensor and evaluated on a different sensor, another test scene acquired by ERS-1 over La Coruna, Spain, during an oil spill in December 1992 in VV polarization is used. Contrary to Sentinel-1, ERS-1 raw data is not compressed and can be directly used in the compression methods without [20] adaptation.

B. Block Adaptive Quantization (BAQ)

BAQ is a data compression technique widely used in SAR systems to reduce the volume of the acquired SAR raw data while preserving essential information. The main idea behind BAQ is to divide the SAR image into blocks of pixels and perform quantization on each block independently. This allows the quantization step size to be adaptively adjusted for each block based on the local characteristics of the data to improve the compression efficiency [4], [27], [28].

BAQ divides the SAR image into non-overlapping blocks of pixels. For each block, local statistics are estimated to determine the optimal quantization step size. Commonly used statistics include mean, variance, or maximum magnitude. A quantization step size is determined for each block, based on the estimated local statistics and defines the intervals into which the CV pixels will be mapped during data compression. The CV pixels in each block are quantized by mapping them into the predefined intervals according to the calculated step size. During data decompression, the quantized data is dequantized to restore the original CV pixels.

Several variations of BAQ have been developed over the years to enhance its performance, such as Entropy Constrained Block Adaptive Quantization [29], Performance Optimized Block Adaptive Quantization [4], Block Adaptive Vector Quantization [30], and Flexible Dynamic Block Adaptive Quantization (FDBAQ) [26].

BAQ as a standard and most commonly used method for SAR raw data compression onboard the past and current SAR missions, including Sentinel-1 and TerraSAR-X, is selected as a comparison method in this study.

C. JPEG2000

JPEG2000 is a wavelet-based image compression standard, developed by the Joint Photographic Experts Group (JPEG) committee to replace the original JPEG system [5]. JPEG2000 is an efficient, flexible, and interactive image compression method, and offers adaptability and control for a wide range of applications [31], [32]. Simplicity and computational efficiency of JPEG2000 makes it a practical choice for various use cases, including detected SAR data compression [7], [33].

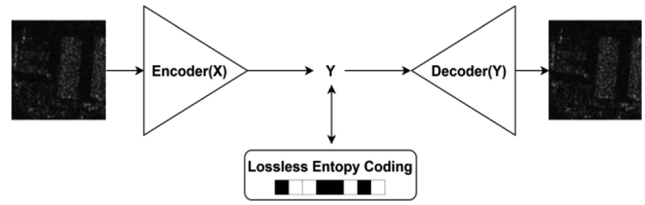

Fig. 1. A high-level schematic overview of neural data compression models.

SAR raw data have a very low correlation but it has been shown in the previous studies [6] that a lowpass filtered SAR raw data contains some correlation which can be exploited for compression. Although JPEG2000 is not inherently designed for CV data, experiments in [6] showed that its wavelet filters can effectively utilize such correlation for SAR raw data compression when applied separately to the real and imaginary components.

D. Neural Data Compression

In the lossy data compression algorithms usually an alternative representation of the image in another space is found to be quantized, instead of the image pixel intensities [13]. The transformation method for the conventional data compression algorithms, including JPEG2000, is fixed and cannot be adapted to the statistics of the data. However, in the neural data compression methods, a neural network architecture is trained to transform the data into the embedded features (i.e., the alternative representation), considering (i.e., learned from) the statistics and distribution of the data. Since this transformation (and the following quantization) is responsible for the lossy part of the data compression, neural data compression methods provide a more adaptive transformation model, hence lower data loss [14].

After the quantization, the image is represented in a discrete-valued manner with a set of N symbols $s = (s_1, \ldots, s_N)$ and it can be losslessly compressed using an entropy coding method, such as arithmetic coding, to obtain a bitstream. The entropy model uses a prior probability model of the quantized representation, which is known to both encoder and decoder. Fig. 1 shows a high-level schematic overview of neural data compression models. This model resembles with the autoencoder networks, although autoencoders are not the only architectures used for neural data compression [14], [34].

As shown in Fig. 1, generally, neural data compression networks consist of three main parts, an encoder which maps the input image into the latent embedded features, a decoder that reconstructs the data from the embedded features, and an entropy coder that estimates the real (unknown) distribution of the embedded features with an entropy model and uses an entropy coding algorithm (such as adaptive arithmetic coding), which losslessly encodes them into a bitstream [35].

In a lossy neural data compression problem, the aim is to minimize the distortion error caused by representing the data X with the encoder and decoder architectures as the reconstructed data $\tilde{X}$, and simultaneously, reducing the required average number of bits to losslessly encode the latent representation of the data Y.

Rate-Distortion (RD) theory defines the limits on the possible data compression rate for any given distortion [36]. Consequently, the RD loss function is commonly used for training neural data compression networks. In this section, the rate-distortion theory and loss function for training the data compression networks is reviewed, and later, the principles of the CV deep architectures for developing the CV neural data compression are introduced. Finally, the architecture of the CV autoencoder-based data compression network is presented.

1) Rate-Distortion Loss in Information Theory: In the lossy neural data compression models, RD loss $\mathcal{L}_{RD}$ shown in (1), is used. RD loss consists of two main terms. Rate loss $\mathcal{L}_R$ which estimates the minimum number of bits required on average to store the embedded bitstream, and Distortion loss $\mathcal{L}_D$ which is the pairwise distortion metric between the input and the output images. The weight parameter λ is used to control and adjust the compression rate, according to a specific use case and application.

$$\mathcal{L}_{RD} = \mathcal{L}_R + \lambda \mathcal{L}_D \tag{1}$$

The real distribution of the embedded features is unknown as it arises from both the distribution of the input image, and the encoding method which is used to infer the embedded representation. As a result, the rate term in the loss function is estimated using the Shannon cross-entropy between the real distribution $q(s)$ and the estimated distribution model $p(s)$ of the symbols in the embedded features, as shown in (2).

$$\mathcal{L}_R = E_{s\sim q}\left[-\log_2 p\left(s\right)\right] \tag{2}$$

The rate term is optimized during the training of the compression network through minimizing the cross entropy between the real and the estimated distribution of the symbols in the discrete embedded features. It should be noted that our purpose is to losslessly compress the entire set s at once, instead of compressing each part s_i separately. We assume that the symbols representing each image are independent and identically distributed (i.i.d.). As a result, we want to model the symbols stream as a random variable $s = (s_1, \ldots, s_N)$, in which each s_i is also a random variable from the finite set of s. The joint entropy of the symbols' s, denoted as $H(q(s))$, can be defined as shown in (3)

$$\begin{aligned} H\left(q\left(s\right)\right) = H\left(q_1\left(s_1\right)\right) + H\left(q_2\left(s_2\right)\left|q_1\left(s_1\right)\right.\right) + \ldots \\ + H\left(q_N\left(s_N\right)\left|q_1\left(s_1\right), \ldots, q_{N-1}\left(s_{N-1}\right)\right.\right) \end{aligned} \tag{3}$$

We want to losslessly encode s into the bitstream that can be recovered exactly but the distribution of the symbols $q(s)$ is the probability of many different occurrences of s and there are $|s|^N$ of such occurrences [14].

If we denote the minimum code length of the compressed bitstream with L^*,

$$H(q\left((s)\right) \leq L^* < H(q\left((s)\right) + 1 \tag{4}$$

In this equation, L^* is the expected code length for one occurrence of s. While the code length might be shorter than $H(q((s))$ for a particular occurrence, we cannot go below the entropy in expectation for the whole stream of s [14].

Due to the unknown real distribution $q(s)$ of the embedded features, we use the estimated distribution model $p(s)$. However, using the estimated distribution $p(s)$ for encoding the symbols s with the $q(s)$ distribution will lead to the overhead code length $\bar{L}$ equal to the Kullback–Leibler (KL) divergence of $q(s)$ and $p(s)$, as shown in (5)

$$\bar{L} = D_{KL}\left(q\left(s\right), p\left(s\right)\right) \tag{5}$$

And as a result, the overall expected code length r is the summation of L^* and $\bar{L}$, as shown in (6)

$$\begin{aligned} r &= L^* + \bar{L} < 1 + H\left(q\left(s\right)\right) + D_{KL}\left(q\left(s\right), p\left(s\right)\right) \\ &= 1 + E_{s\sim q}\left[-\log_2 p\left(s\right)\right] \end{aligned} \tag{6}$$

The last term in (6) equals to the Shannon cross entropy in (2). Consequently, minimizing the cross entropy in $\mathcal{L}_R$ minimizes the expected code length or the rate term of the rate-distortion loss function [14].

Furthermore, the distortion term in the loss function is used to minimize the data loss during the transformation and quantization of the lossy data compression. Distortion term can be any similarity metric between the input and the reconstructed image. Well-known Mean Square Error (MSE) measure is used in this study as the distortion metric, as shown in (7).

$$\mathcal{L}_D = \|x - \tilde{x}\|^2 \tag{7}$$

There is a trade-off between the rate and distortion terms where a higher rate allows for a lower distortion, and vice versa. So, the loss function used for training the data compression network is the weighted sum of these two terms. The λ parameter in (1) is the weight on the distortion term that controls the trade-off between these two losses and enables us to achieve different bitrates for different applications.

2) Complex-Valued Deep Architectures and CV Neural Data Compression: CV deep architectures are developed to deal with the complex-valued nature of data, such as SAR data, and exploit the amplitude and phase information in these data, simultaneously, while preserving the correlation and coherence between the real and imaginary components of the CV data. Applicability and efficiency of the CV deep architectures for different SAR applications have been tested in the previous studies [17], [18], [19], [25], and demonstrated the ability of the CV networks to learn the complex distribution of SAR data and preserve the original properties, complex coherence and physical attributes of SAR data.

The conversion of the necessary operators for deep networks from real domain to the complex domain are provided in [17], including the CV convolutional, linear, pooling and normalization layers, and various activation functions, as well as the CV backpropagation method for training the CV deep networks. Complex partial derivative is used to develop the CV backpropagation, based on the Stochastic Gradient Descent (SGD). The partial derivative of a complex function $f(z)$ with respect to z and $\bar{z}$, while $z = a + jb \in \mathbb{C},\ (a, b) \in \mathbb{R}^2$, according to the Wirtinger calculus [37] is defined as (8)

$$\frac{\partial f}{\partial z} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial a} - j\frac{\partial f}{\partial b}\right), \frac{\partial f}{\partial \bar{z}} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial a} + j\frac{\partial f}{\partial b}\right) \tag{8}$$

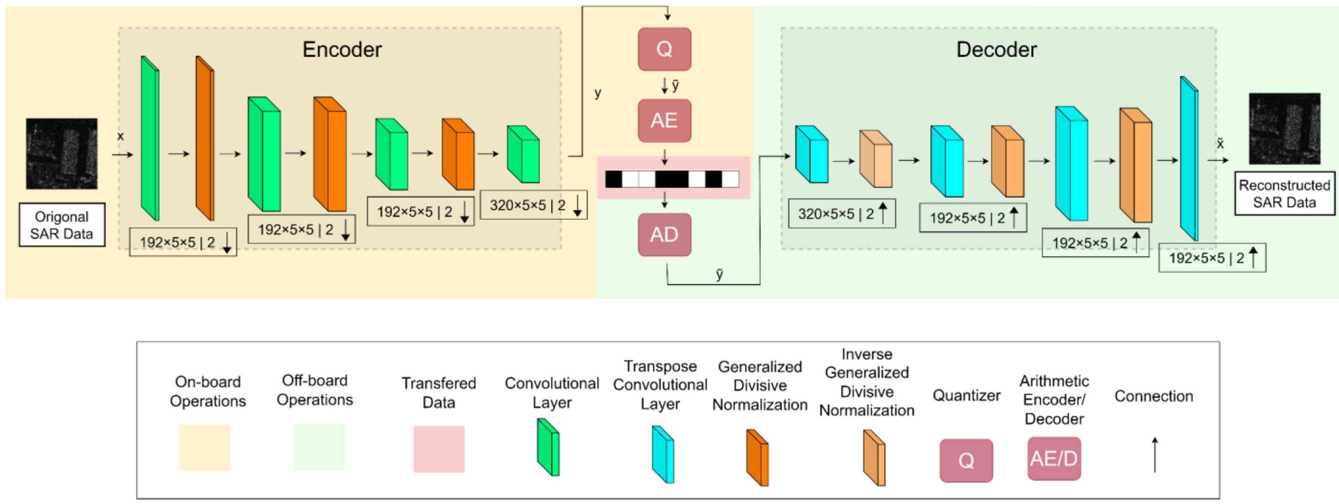

Fig. 2. Architecture of the proposed autoencoder-based compression model. In this figure, below each convolutional or transpose convolutional layer, a box is showing "number of filters" × "kernel height" × "kernel width" | "stride size". In these boxes, downward arrows show downsampling in the convolutional layers and the upward arrows show upsampling in the transpose convolutional layers. Moreover, all the convolutional layers in the encoder have zero padding of 2 and all the transpose convolutional layers in the decoder have zero padding of 2 and out padding of 1.

The CV operators are utilized in this study to define and train the CV data compression network, based on the autoencoder architectures, for SAR raw data compression.

The architecture of the proposed model consists of three main parts, encoder, entropy model, and decoder. Fig. 2 shows the architecture of the proposed autoencoder-based data compression network. In this figure, below each convolutional or transpose convolutional layer, a box is showing “number of filters” × “kernel height” × “kernel width” | “stride size”. In these boxes, downward arrows show downsampling in the convolutional layers and the upward arrows show upsampling in the transpose convolutional layers. All the convolutional layers in the encoder have zero padding of 2 and all the transpose convolutional layers in the decoder have zero padding of 2 and out padding of 1.

In this architecture, the encoder comprises of several CV convolutional layers followed by CV Generalized Divisive Normalization (GDN) layers. The encoder represents the input image patch x with the size of 256×256 pixels in the latent space as the embedded features y. Later a quantization module quantizes the embedded features into a discrete-valued representation $\tilde{y}$. Since the derivative of the quantization function is zero almost everywhere, during the training, the quantization module is replaced by additive uniform noise to maintain the gradient for the backpropagation algorithm and train the network [13]. However, after training, actual quantization is used.

The quantized embedded feature maps $\tilde{y}$ are discrete-valued and can be losslessly compressed into a bitstream using an entropy coding method, arithmetic encoder in this study. The resulting bitstream is the compressed data and is transferred or stored.

To decompress and reconstruct the data, the entropy decoder with the same entropy model as the entropy coder, is used to decode the compressed bitstream and recover the latent features. Later, the CV decoder network, with similar CV layers to the CV encoder network (without the activation function in the output layer), in reverse mode, is used to reconstruct the SAR raw data from the latent features.

III. Experimental Results

The workflow to conduct the experiments is shown in Fig. 3. Due to the FDBAQ compression of Sentinel-1 SAR raw data, the adaptation method proposed in [20] is used to preprocess the SAR raw data before employing the data compression methods. BAQ, JPEG2000, and the CV autoencoder-based data compression methods are applied to the adapted SAR raw data. The decompressed data are processed to obtain the Single Look Complex (SLC) SAR images and the evaluation metrics are measured between the SLC images before and after compression. It should be noted that during the training of the network, distortion loss is computed between the input and output SAR raw data, as the SLC products are not available while training the network. In the following subsections, we quantitatively and qualitatively compare the performance of the CV autoencoder-based compression method with BAQ and JPEG2000, analyze the performance gain from the CV network, and evaluate the generalizability of the proposed CV architecture.

A. Quantitative Performance Comparison

The λ parameter in RD loss (1) regulates between the rate and distortion in the loss function. Higher λ forces the network to lower the data loss and reconstruct the data with higher quality, in expense of a higher bitrate. On the other hand, a lower λ value achieves lower bitrates (i.e., higher compression rate) but with higher data loss. The network shown in Fig. 2 is trained with different λ values to obtain different compression rates.

Three different measures, including Signal to Quantization Noise Ratio (SQNR), phase error and complex coherence, are measured between the SLC images before and after compression

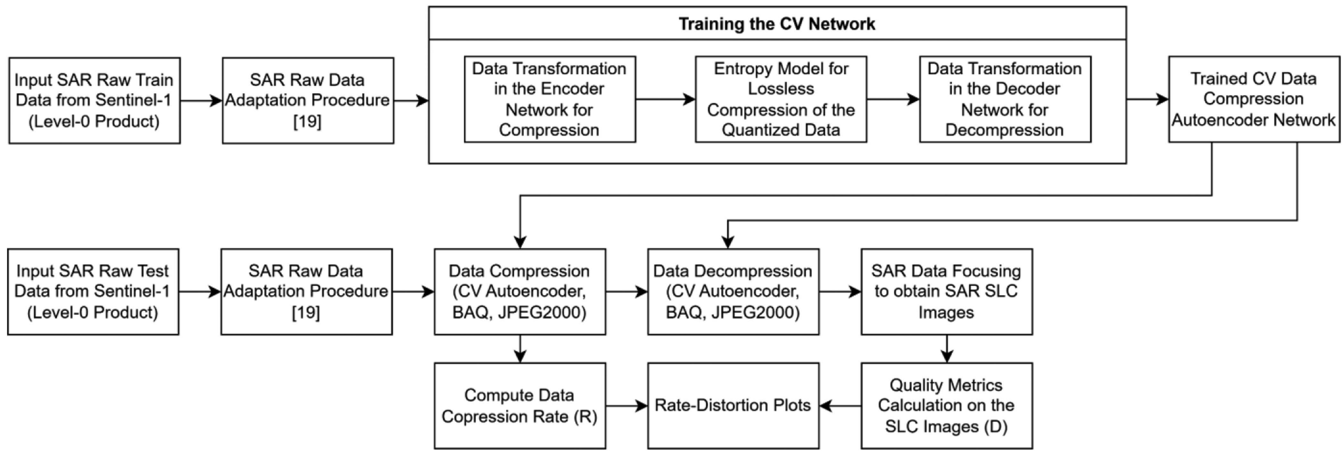

Fig. 3. Workflow of the experiments. Note that while training the network, both rate and distortion are computed on the raw data but while performance assessment, the rate is computed on the compressed SAR raw data, while the distortion is computed on the final product (single look complex (SLC) SAR images) after focusing the input and output SAR raw data.

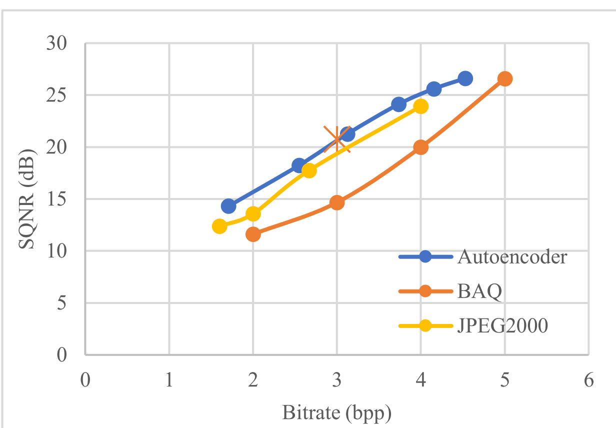

Fig. 4. Comparative analysis of the CV autoencoder, BAQ, and JPEG200 data compression with SQNR metric. The orange × shows the unexpected behavior of BAQ with 3 bpp as explained below.

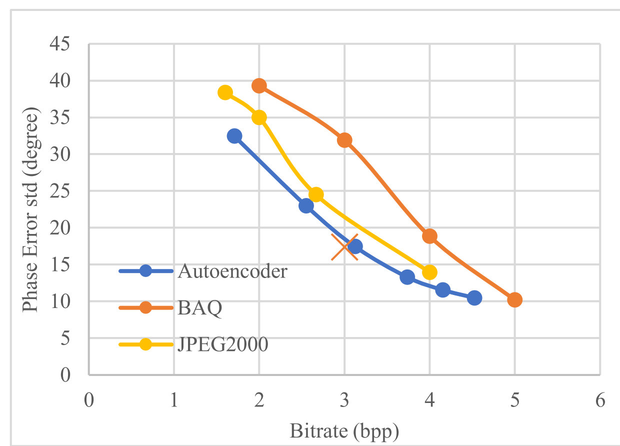

Fig. 5. Comparative analysis of the CV autoencoder, BAQ, and JPEG200 compression with phase error metric. The orange × shows the unexpected behavior of BAQ with 3 bpp as explained below.

of the raw data with BAQ, JPEG2000, and CV autoencoder-based data compression methods. The results are shown in Figs. 4, 5, and 6, respectively.

It should be noted that the final bitrate obtained from the trained CV network depends on the input data. A perfectly optimized network should learn what information from the input data should be preserved in the embedded features for better data reconstruction, lower loss, and higher compression rate. As a result, the size of the information preserved for each input patch is different and depends on the heterogeneity/homogeneity of the patch. In another words, each compressed patch has a different bitrate (based on the content) and the reported bitrate values are the average bitrate for all of the patches from the test scene.

The results presented in Figs. 4, 5, and 6 highlight the superior performance of the proposed CV autoencoder-based compression method for SAR raw data across all tested bitrates. These findings emphasize the effectiveness of the proposed

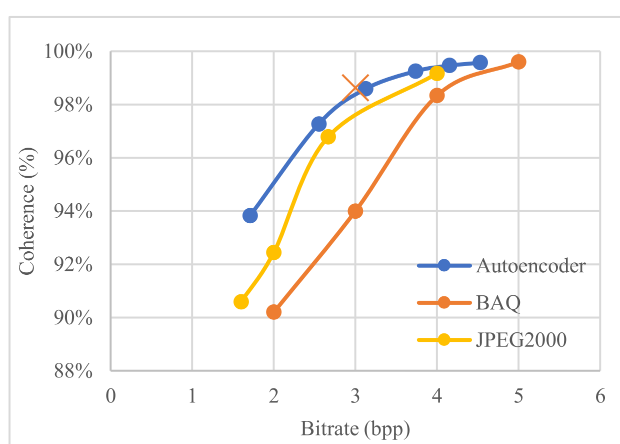

Fig. 6. Comparative analysis of the CV autoencoder, BAQ, and JPEG200 compression with complex coherence metric. The orange × shows the unexpected behavior of BAQ with 3 bpp as explained below.

TABLE I
INTERPOLATED SQNR VALUES FOR 2, 3, AND 4 BPP FOR THE CV AUTOENCODER-BASED (CAE), BAQ, AND JPEG2000 (JP2) COMPRESSION METHODS AND THE CORRESPONDING GAIN OF THE CAE WITH RESPECT TO BAQ AND JP2

bpp	CAE	BAQ	JP2	CAE-BAQ Gain	CAE-JP2 Gain
2	15.9	11.6	14.1	**4.3**	**1.8**
3	20.3	14.7	19.0	**5.7**	**1.3**
4	24.8	20.0	24.0	**4.8**	**0.8**

TABLE II
INTERPOLATED PHASE ERROR VALUES FOR 2, 3, AND 4 BPP FOR THE CV AUTOENCODER-BASED (CAE), BAQ, AND JPEG2000 (JP2) COMPRESSION METHODS AND THE CORRESPONDING GAIN OF THE CAE WITH RESPECT TO BAQ AND JP2

bpp	CAE	BAQ	JP2	CAE-BAQ Gain	CAE-JP2 Gain
2	28.2	39.3	33.8	**11.1**	**5.6**
3	20.4	31.9	23.4	**11.5**	**3.0**
4	12.5	18.8	13.0	**6.3**	**0.5**

TABLE III
INTERPOLATED COMPLEX COHERENCE VALUES FOR 2, 3, AND 4 BPP FOR THE CV AUTOENCODER-BASED (CAE), BAQ, AND JPEG2000 (JP2) COMPRESSION METHODS AND THE CORRESPONDING GAIN OF THE CAE WITH RESPECT TO BAQ AND JP2

bpp	CAE	BAQ	JP2	CAE-BAQ Gain	CAE-JP2 Gain
2	95.4%	90.2%	92.4%	**5.2%**	**3.0%**
3	97.4%	94.0%	96.3%	**3.4%**	**1.1%**
4	99.3%	98.3%	99.1%	**1.0%**	**0.2%**

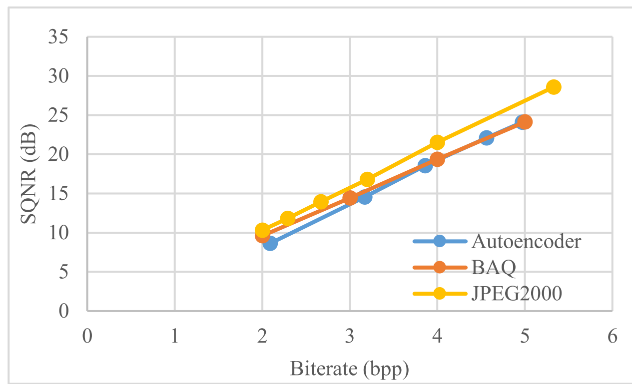

Fig. 7. Generalizability evaluation of the CV autoencoder. The CV model is trained on Sentinel-1 data and tested on ERS-1 data.

approach, demonstrating the significant potential of CV deep learning-based methods for SAR raw data compression.

While applying the BAQ to the raw data, an unexpected behavior is observed for BAQ with 3 bit per pixel (bpp). The results from the BAQ with 3 bpp (shown with the Orange × in Figs. 4, 5, and 6) are much better than the expected results, even slightly better than BAQ with 4 bpp. With further analysis, we concluded that this behavior is due to the FDBAQ compression of the available Sentinel-1 raw data, and there is a coincidental similarity between the quantization steps of the raw data and BAQ with 3 bpp. After adding random noise to the raw data and employing the adaptation procedure [20], the results are as expected (shown in the Figs. 4, 5, and 6). This effect demonstrates the necessity and effectiveness of the SAR raw data adaptation procedure [20].

B. Performance Gain

To better compare the data compression methods and assess the performance gain from the CV autoencoder-based data compression in comparison to BAQ and JPEG2000, the evaluation metrices for all the compression methods are interpolated for 2, 3, and 4 bpp bitrates. Tables I, II, and III represent the interpolated metrices and the corresponding gain of the CV autoencoder-based compression in comparison to the BAQ and JPEG2000, respectively for SQNR, phase error and complex coherence metrics.

The CV autoencoder obtained about 4-6 dB higher SQNR than BAQ and about 1-2 dB higher SQNR than JPEG2000. The superior performance of the CV autoencoder is evident also in the phase error and complex coherence metrices. The results shown in Figs. 4, 5, 6 and 7, and Tables I, II, and III demonstrate the superior performance of the CV autoencoder-based compression method for SAR raw data compression, with respect to the BAQ and JPEG2000.

Moreover, the main purpose of the data compression algorithms is to reduce the bitrate of the data for a target performance. As a result, we explored how much the CV autoencoder-based data compression has reduced the bitrate of the raw data for a target SQNR performance. Looking at Fig. 4 with a target SQNR performance of 15 dB, the CV autoencoder in comparison to BAQ, reduced the bitrate of the compressed data by about 1.3 bpp (1.8 and 3.1 bpp, respectively) which is about 42% improvement. With the target SQNR performance of 20 dB, the CV autoencoder in comparison to BAQ, reduced the bitrate of the compressed data by about 1.1 bpp (2.9 and 4 bpp, respectively) which is about 27% improvement. The noticeable improvement of the data compression rate without any additional data loss indicates the immense potential of the CV deep networks for efficient SAR raw data compression applications.

C. Generalizability

In the previous sections, the proposed CV autoencoder is trained on three diverse scenes acquired with Sentinel-1 and its performance is tested for compressing a separate Sentinel-1 scene with diverse landcovers. In this section, we inspect the generalizability of the proposed method when it is trained on the scenes from one satellite, and applied to a scene acquired by

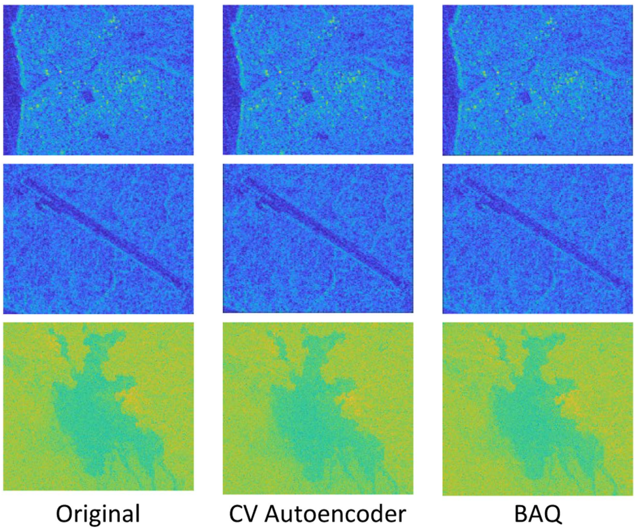

Fig. 8. Output SLC images before and after compression with the proposed CV autoencoder-based and BAQ compression methods, over Sao Filipe city (first row) and the airport (second row) from the Sentinel-1 test scene and over La Coruna / Aegean Sea oil spill (third row) from the ERS-1 test scene.

a different satellite. An ERS-1 scene acquired over La Coruna, Spain, during an oil spill in December 1992 is used for this purpose. It should be noted that the ERS-1 scene is acquired in VV polarization, while the training Sentinel-1 scenes are in HH polarization with different imaging mode and imaging geometry (e.g., incidence angle).

As shown in Fig. 7, the proposed CV autoencoder achieved comparable performance to the BAQ and JPEG2000 techniques, without any finetuning and retraining. Considering the significant differences between the training and testing scenes for the CV autoencoder, the promising performance shows the generalizability of the proposed method. This performance can be further improved by finetuning the CV autoencoder for the target sensor, as well as improvements in the architecture of the model.

D. Qualitative Performance Comparison

Output SLC images over two zoomed-in areas in the Sentinel-1 test scene, Sao Filipe city and the airport, and one zoomed-in area in the ERS-1 test scene, La Coruna / Aegean Sea oil spill, before and after compression with the proposed CV autoencoder and BAQ are shown in Fig. 8. In comparison to BAQ, the SLC image after compression with the proposed method preserved more details of the original image and has a sharper and more similar colour composition to the original image.

The visual differences between these images are not vividly visible, due to the low resolution and size of the images (better visible on the bright urban structures and the airport runway). To better manifest the superior performance of the proposed method, Fig. 9 shows the histogram of the normalized magnitude differences between the compressed and the original uncompressed image for the CV autoencoder and BAQ methods in the both test scenes. With Sentinel-1 data, the proposed CV autoencoder-based compression method has a noticeable lower magnitude difference which indicates the better reconstruction of the SAR data and lower data loss. Comparable performance of the proposed method to BAQ on the ERS-1 data is shown in the second histogram in Fig. 9 which reflects the generalizability of the proposed CV autoencoder-based data compression architecture.

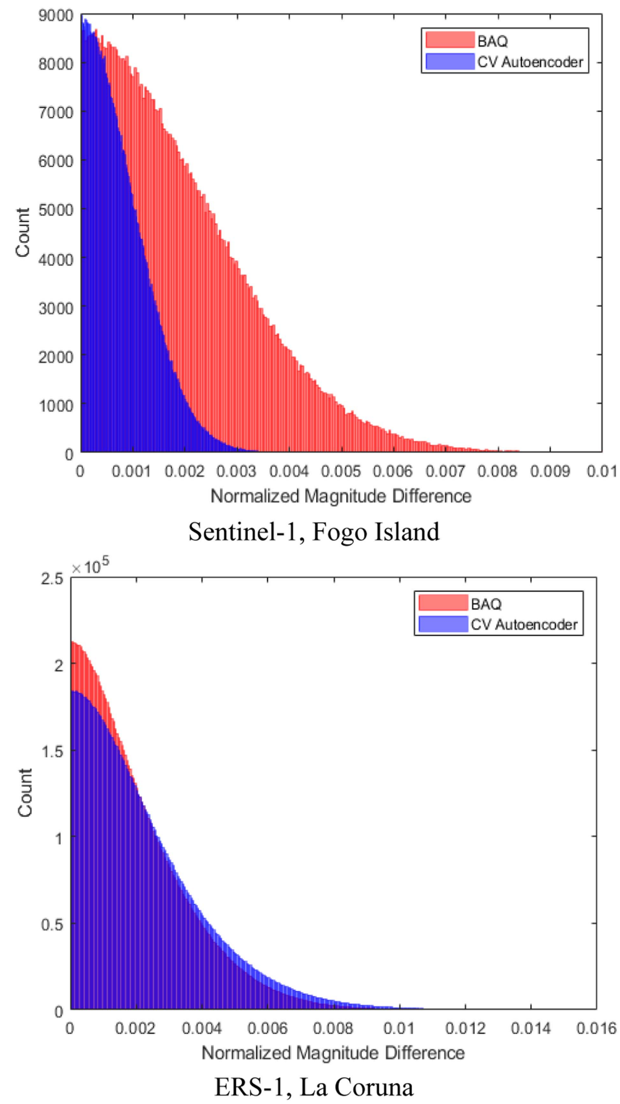

Fig. 9. Histogram of the normalized magnitude differences between the compressed and uncompressed original SAR images for the CV autoencoder and BAQ methods in Sentinel-1 and ERS-1 test scenes.

IV. Conclusion

SAR raw data compression problem is explored in this study. Neural data compression methods, based on deep architectures are extended to the complex domain and a CV autoencoder-based data compression is designed. BAQ and JPEG2000 methods are employed for SAR raw data compression, as standard data compression techniques, and the results are compared with that of the developed CV autoencoder-based data compression architecture in terms of the quantitative and qualitative metrics, performance gain and generalizability.

The adapted quasi-uniformly quantized SAR raw data are compressed using the CV autoencoder-based data compression, BAQ and JPEG2000 algorithms and three quality metrics, including SQNR, phase error and complex coherence, are calculated to compare the performance of the data compression methods. The obtained results demonstrated the superiority of the CV autoencoder-based data compression and showed the immense potential of the CV neural compression methods for SAR raw data compression onboard the next generation SAR missions.

In conclusion, the findings of this study demonstrated the competency and potential of the CV deep architectures for SAR raw data compression. CV networks can learn the physical data model and preserve the original properties and attributes of SAR data. Due to these qualifications CV architectures are competent to handle SAR raw data with peculiar characteristics. These findings unfold new perspectives and pave the way for further advancements of the CV architectures in the future studies for various SAR applications and future advanced SAR satellite missions.

References

[1] D. Geudtner, M. Tossaint, M. Davidson, and R. Torres, "Copernicus Sentinel-1 next generation mission," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2021, pp. 874–876.

[2] M. Davidson, L. Iannini, R. Torres, and D. Geudtner, "New perspectives for applications and services provided by future spaceborne SAR missions at the European Space Agency," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2022, pp. 4720–4723.

[3] D. Geudtner et al., "Copernicus and ESA SAR missions," in *Proc. IEEE Radar Conf.*, 2021, pp. 1–6.

[4] M. Martone, N. Gollin, P. Rizzoli, and G. Krieger, "Performance-optimized quantization for SAR and InSAR applications," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, 2022, Art. no. 5229922.

[5] D. S. Taubman, M. W. Marcellin, and M. Rabbani, "JPEG2000: Image compression fundamentals, standards and practice," *J. Electron. Imag.*, vol. 11, no. 2, pp. 286–287, 2002.

[6] R. M. Asiyabi et al., "On the use of JPEG2000 for SAR raw data compression," in *Proc. Eur. Conf. Synth. Aperture Radar EUSAR*, 2024, pp. 249–253.

[7] R. Kozhemiakin, S. Abramov, V. Lukin, B. Djurović, I. Djurović, and M. Simeunović, "Strategies of SAR image lossy compression by JPEG2000 and SPIHT," in *Proc. 6th Mediterranean Conf. Embedded Comput.*, 2017, pp. 1–6.

[8] J. Li and L. Chang, "A SAR image compression algorithm based on Mallat tower-type wavelet decomposition," *Optik*, vol. 126, no. 23, pp. 3982–3986, 2015.

[9] B. Dheepa, R. Nithya, N. Nishavithri, K. Vinoth, and K. Balaji, "Directional lifting wavelet transform based SAR image compression," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 3, pp. 3700–3707, May-Jun. 2020.

[10] E. Magli, G. Olmo, and B. Penna, "Wavelet-based compression of SAR raw data," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2002, vol. 2, pp. 1129–1131.

[11] X. Zhan and R. Zhang, "Complex SAR image compression using entropy-constrained dictionary learning and universal trellis coded quantization," *Chin. J. Electron.*, vol. 25, no. 4, pp. 686–691, 2016.

[12] X. Zhan, R. Zhang, D. Yin, and C. Huo, "SAR image compression using multiscale dictionary learning and sparse representation," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, no. 5, pp. 1090–1094, Sep. 2013.

[13] J. Ballé, D. Minnen, S. Singh, S. J. Hwang, and N. Johnston, "Variational image compression with a scale hyperprior," in *Proc. the Int. Conf. on Learn. Representations*, Vancouver Canada, 2018, pp. 1–10.

[14] F. Mentzer, "Neural image compression: Lossy and lossless algorithms," Ph.D. dissertation, ETH Zurich, 2021.

[15] Q. Xu et al., "Synthetic aperture radar image compression based on a variational autoencoder," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, 2022, Art. no. 4015905.

[16] C. Fu, B. Du, and L. Zhang, "SAR image compression based on multiresblock and global context," *IEEE Geosci. Remote Sens. Lett.*, vol. 20, 2023, Art. no. 4002105.

[17] R. Mohammadi Asiyabi, M. Datcu, A. Anghel, and H. Nies, "Complex-valued end-to-end deep network with coherency preservation for Complex-valued SAR data reconstruction and classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 5206417, doi: 10.1109/TGRS.2023.3267185.

[18] R. M. Asiyabi, M. Datcu, A. Anghel, and H. Nies, "Complex-valued autoencoders with coherence preservation for SAR," in *Proc. 14th Eur. Conf. Synthetic Aperture Radar*, 2022, pp. 1–6.

[19] R. Mohammadi Asiyabi, M. Datcu, H. Nies, and A. Anghel, "Complex-valued vs. real-valued convolutional neural network for Polsar data classification," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2022, pp. 421–424.

[20] R. M. Asiyabi et al., "Adaptation of decoded Sentinel-1 SAR raw data for the assessment of novel data compression methods," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2024, pp. 2541–2545.

[21] P. Potin et al., "Copernicus Sentinel-1 constellation mission operations status," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2019, pp. 5385–5388.

[22] A. Ghorbanian, S. Zaghian, R. Mohammadi Asiyabi, M. Amani, A. Mohammadzadeh, and S. Jamali, "Mangrove ecosystem mapping using Sentinel-1 and Sentinel-2 satellite images and random forest algorithm in Google Earth Engine," *Remote Sens.*, vol. 13, no. 13, 2021, Art. no. 2565.

[23] M. A. Iqbal, A. Anghel, and M. Datcu, "Doppler centroid estimation for ocean surface current retrieval from Sentinel-1 SAR data," in *Proc. 18th Eur. Radar Conf.*, 2022, pp. 429–432.

[24] O. Ghozatlou, M. Datcu, and B. Chapron, "Gan-based ocean pattern SAR image augmentation," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2023, pp. 4056–4059.

[25] M. A. Iqbal, R. Mohammadi Asiyabi, O. Ghozatlou, M. Datcu, and A. Anghel, "Towards complex-valued deep architectures with data model preservation for sea surface current estimation from SAR data," in *Proc. 20th Int. Conf. Content-Based Multimedia Indexing*, 2023, pp. 146–152, doi: 10.1145/3617233.3617271.

[26] E. Attema et al., "Flexible dynamic block adaptive quantization for Sentinel-1 SAR missions," *IEEE Geosci. Remote Sens. Lett.*, vol. 7, no. 4, pp. 766–770, Oct. 2010.

[27] R. Kwok and W. T. K. Johnson, "Block adaptive quantization of Magellan SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 4, pp. 375–383, Jul. 1989.

[28] D. Lancashire, B. Barnes, and S. Udall, "Block adaptive quantization," U.S. Patent US 6 255 987, 2001. [Online]. Available: http://www.patentlens.net/patentlens/patent/US6255987/

[29] T. Algra, "Data compression for operational SAR missions using entropy-constrained block adaptive quantisation," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2002, vol. 2, pp. 1135–1139.

[30] A. Moreira and F. Blaser, "Fusion of block adaptive and vector quantizer for efficient SAR data compression," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 1993, vol. 4, pp. 1583–1585.

[31] D. S. Taubman and M. W. Marcellin, "JPEG2000: Standard for interactive imaging," *Proc. IEEE*, vol. 90, no. 8, pp. 1336–1357, Aug. 2002.

[32] C. Bako, "JPEG 2000 image compression," *BROADCAST Eng.-Indianap. THEN Overl. PARK Kans.-*, vol. 48, no. 2, p. 77, 2006.

[33] P. Zhou and B. Zhao, "Novel scheme for SAR image compression based on JPEG2000," in *Proc. 9th Int. Conf. Electron. Meas. Instrum.*, 2009, pp. 4–206–4–209.

[34] E. Agustsson, M. Tschannen, F. Mentzer, R. Timofte, and L. V. Gool, "Generative adversarial networks for extreme learned image compression," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2019, pp. 221–231.

[35] Y. Yang, S. Mandt, and L. Theis, "An introduction to neural data compression," *Found. Trends Comput. Graph. Vis.*, vol. 15, no. 2, pp. 113–200, 2023.

[36] C. E. Shannon, "Coding theorems for a discrete source with a fidelity criterion," *IRE Nat. Conv. Rec.*, vol. 4, pp. 142–163, 1959.

[37] W. Wirtinger, "Zur formalen theorie der funktionen von mehr komplexen veränderlichen," *Math. Ann.*, vol. 97, no. 1, pp. 357–375, 1927.

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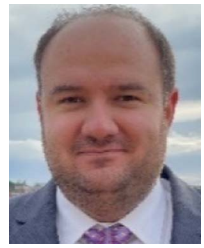

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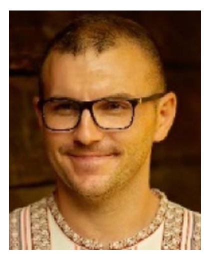

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