COMPLEX-VALUED AUTOENCODER FOR MULTI-POLARIZATION SLC SAR DATA COMPRESSION WITH SIDE INFORMATION

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ABSTRACT

Recent advances in Synthetic Aperture Radar (SAR) sensors have enabled the acquisition of very high-resolution images with wide swaths, large bandwidth and in multiple polarization channels. As a result of the significant increase of SAR data size, an effective compression of the acquired data is of paramount importance. However, conventional data compression methods demonstrate limited effectiveness when applied to SAR data. In order to tackle this problem, in this study, a Complex-Valued (CV) end-to-end deep learning-based architecture based on convolutional autoencoders is proposed to compress Single Look Complex (SLC) SAR data. By relying on dual polarization SAR data, one of the polarization channels of the data is used as the side information to assist the reconstruction of the compressed channel with lower data loss. The obtained results demonstrate the remarkable potential and capability of CV deep learning-based methods for SAR data compression.

***Index Terms*—** Complex-valued networks, Data compression, Deep learning, Synthetic Aperture Radar (SAR)

1. INTRODUCTION

Innovative advanced SAR imagery techniques have enabled SAR systems to acquire very high resolution images with wide swaths, large bandwidth and in multiple polarization channels [1]. The improvements of the SAR system capabilities also imply a significant increase of SAR data acquisition rates, such that efficient and effective compression methods become necessary. However, conventional compression methods do not satisfy the requirements for the effective SAR Single Look Complex (SLC) data compression for several reasons:

- SLC SAR data is in the complex domain by nature, whereas most of the conventional compression methods do not support complex-valued signals.
- The physical model of the SAR data has to be preserved during the compression procedure.
- Phase component of SAR data is important in many applications, especially Interferometric SAR (InSAR). Phase information of the complex-valued SAR data has to be maintained.

The abovementioned reasons and the other peculiarities of SAR data, such as large dynamic range, inherent speckle effects, and the spatial correlation, require the development of novel compression methods for compressing complex-valued SAR data, considering its unique characteristics.

Several studies have applied different methods for SAR data compression, mostly only considering SAR amplitude images, for instance, optical compression standard methods such as JPEG2000 and SPIHT, wavelet transform-based methods [2]–[4], as well as machine learning and dictionary learning-based methods such as entropy-constrained dictionary learning algorithm (ECDLA) [5], [6]. Deep learning techniques have achieved remarkable results in many different fields and are gradually attracting interest for visual data compression. In this context, autoencoders are widely used for lossy image compression, mostly based on quantization and reducing the bitrate of the image data, including detected SAR images [7]–[9]. Furthermore, Distributed Source Coding (DSC) in Information Theory is used for reducing the data loss in image compression of computer vision applications [10]. In DSC, side information is often used to assist the network to reconstruct the compressed data.

One of the main drawbacks of the deep learning-based compression methods is that SLC SAR data is in complex domain by nature, whereas most of the developed deep learning models are in real domain [11]. Applying the real-valued deep models to the complex-valued SAR data, disregards the phase information and only exploits the amplitude of the SAR data [11], [12]. In order to tackle this problem and to exploit the amplitude and phase components of the Complex-Valued (CV) SAR data, CV deep architectures have been developed in a number of studies [11]–[15].

In this paper, a complex-valued end-to-end deep architecture is developed, based on the convolutional autoencoders (CV-CAE), to compress the SLC SAR data.

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2. METHODOLOGY

In this section, the theoretical methodology of the proposed model is discussed. First, a brief introduction to the complex-valued deep networks is provided. Later, the proposed method and the network architecture for SAR data compression are introduced.

2.1. Complex-valued deep networks

The real and imaginary components of the SLC SAR data are statistically correlated. The CV model should maintain this correlation to properly preserve and extract the physical information from CV-SAR data [11], [16]. Moreover, the complex correlation coefficient (coherence) of the CV-SAR data conveys important physical properties of the target and SAR system, and should be preserved in the complex model [12]. As a result, a fully CV network with coherence preservation is used in this study [11].

The conversion of the necessary operators for deep networks from real domain to the complex domain are provided in previous literature and the coherence preservation of these networks are evaluated [11], [12]. These CV operators are used in this study for the deep architecture.

In order to train the CV network, backpropagation method, based on Stochastic Gradient Descent (SGD), is converted to the complex domain. Wirtinger calculus [17] has defined the partial derivative of the complex function $f(z)$ with respect to z and $\bar{z}$, while $z = x + jy \in \mathbb{C}, (x, y) \in \mathbb{R}^2$, as (1)

$$\frac{\partial f}{\partial z} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} - j\frac{\partial f}{\partial y}\right), \quad \frac{\partial f}{\partial \bar{z}} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} + j\frac{\partial f}{\partial y}\right) \qquad (1).$$

Using this definition, the CV backpropagation can be defined to train the CV deep network. Further explanations on the CV operators and CV backpropagation can be found in [11].

2.2. Network Architecture

Fig. 1 illustrates the architecture of the proposed method. We assume a multi-polarization channel SAR sensor, where the original SAR image for one of the channels (e.g., HH) is used as the side information for better reconstruction of the other compressed polarization channels (e.g., HV). In this architecture, an encoder maps the input HV polarization channel of the SAR image patch into the embedded latent features, which is then quantized. Since the derivative of the quantization function is zero (almost everywhere), the quantization is replaced by uniform noise during the training. However, during compression (after training) actual quantization is used [7], [8].

The quantized latent features are discrete-valued, and can be losslessly compressed by an entropy coding technique (e.g., arithmetic coding) for storage [8]. Later, the arithmetic decoder reconstructs the latent features from the compressed code. The decoder of the network uses the recovered latent features to reconstruct the SAR image (i.e., decoded HV).

This procedure introduces a certain compression error to the decoded HV polarization channel. As a result, in this study, the second autoencoder is used to exploit the correlation between the polarization channels of SAR data and enhance the reconstructed HV channel. For this purpose, the decoded HV and the original HH channels of the SAR patch are fed into the second autoencoder to reconstruct the HV channel with less compression error.

Rate-distortion loss is used to train the network. The distortion is evaluated by the Mean Square Error (MSE) function. The rate is the expected bitrate of the compressed code which is estimated using the cross entropy of the quantized embedded features [8].

3. EXPERIMENTAL RESULTS

3.1. Dataset

Three StripMap (SM) SLC dual polarization (HH/HV) Sentinel-1 SAR scenes, acquired over Chicago and Huston, USA, and Sao Paulo, Brazil, are selected to consider different landcovers (e.g., various constructed areas, vegetation, agriculture, and water bodies) characterized by diverse data dynamic ranges [18]. No further preprocessing is applied on the SAR data. The selected scenes are divided into the patches of 256×256 pixels. 30,000 and 10,000 patches are randomly selected as the train and evaluation sets, respectively.

3.2. Experimental Results and Discussion

The phase component of SAR data is important in many applications, especially InSAR, and the compression method should preserve the phase information. Moreover, the complex coherence measures the similarity and correlation between two images and quantifies the level of noise in the interferogram. The phase error and coherence over a 5×5 pixels window are computed as the performance evaluation metrices. Fig. 2 and 3 depict the phase error and the coherence between the original and the compressed SAR images with different compression rates. In these plots, the blue curve corresponds to the performance without adding the side information, while the orange curve shows the results after adding the side information.

Furthermore, the SAR images are compressed using the Block Adaptive Quantization (BAQ) algorithm [1]. BAQ is a lossy data compression method, used mostly for raw SAR data. However, the statistics of the SLC and raw SAR data are similar and since BAQ can be applied to CV data (i.e.,

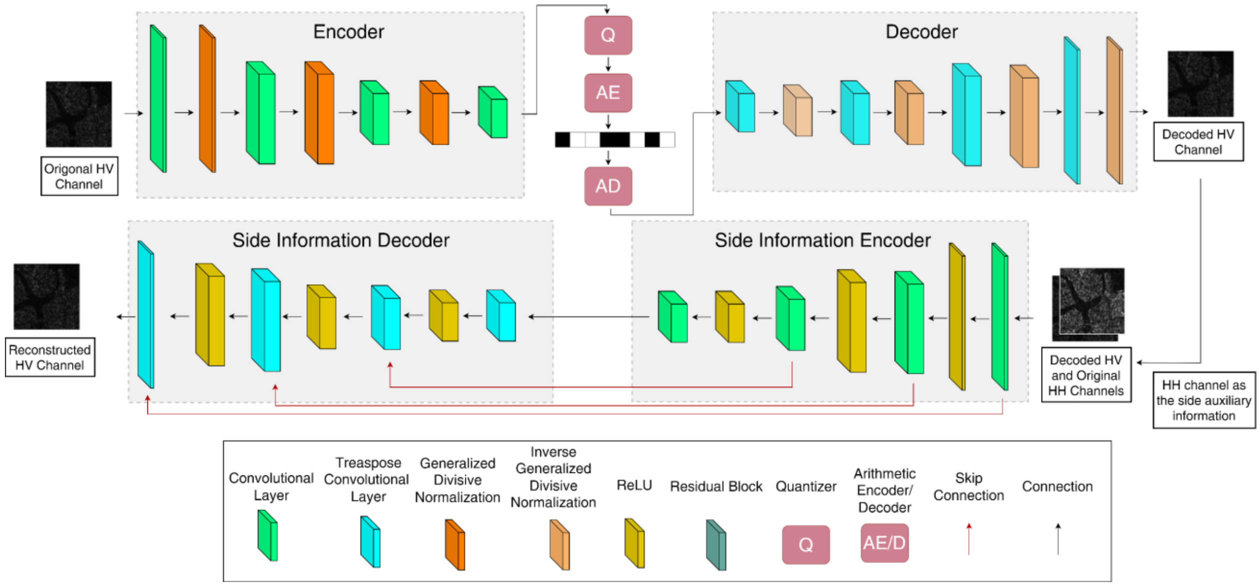

Fig. 1. Architecture of the network. In this architecture, the encoder in the first autoencoder (first row) compresses the SAR image patch into the embedded feature map, which gets quantized and losslessly compressed by an arithmetic encoder. Later, arithmetic decoder recovers the compressed embedded features and the decoder and the second autoencoder (second row) reconstruct the SAR image patch from the decoded embedded features.

similar to the CV network in this study), it is hereby used for comparison.

The CV autoencoder achieves remarkably better results than BAQ for all the considered compression rates. The CV autoencoder compresses the SAR data to about 0.67 bits per pixel (bpp) with only 8.04˚ phase error. The phase error is decreased to 2.7˚ with the 4.06 bpp compression. While BAQ with 4 bpp introduces 10.06˚ phase error to the data.

However, adding the side information does not improve the results, evidently. Only a slight improvement can be noticed in the very low bitrate compressions. The phase error of the 0.67 bpp compression is decreased to 7.9˚ (about 0.14˚ improvement) after adding the side information.

Despite the negligible effect of the side information, the potential of the DSC for SAR data compression is evident. The inability of the side information to improve the results can lie in incompetency of the second autoencoder that have been used to incorporate the side information. The second autoencoder consists of only a few convolutional layers and apparently, the network does not have enough depth to allow the correlation between the polarization channels of SAR data to improve the reconstruction of the HV channel. A more advanced architecture could help to better exploit this correlation and improve the reconstruction of the compressed SAR channel.

Fig. 4 shows the original, reconstructed, coherence, and phase error of a sample SAR patch over an industrial area. The dynamic ranges are limited for better visualization.

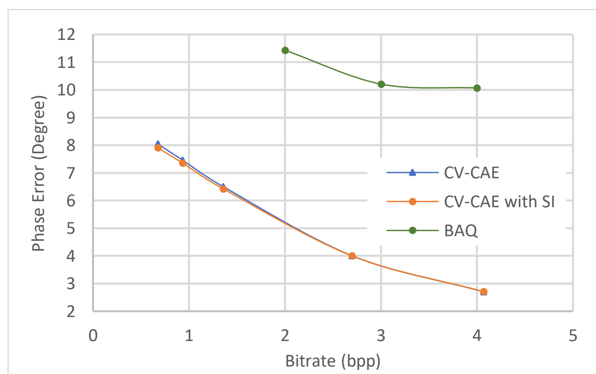

Fig. 2. Phase error between the original and the reconstructed SAR images for different compression rates with CV-CAE and BAQ.

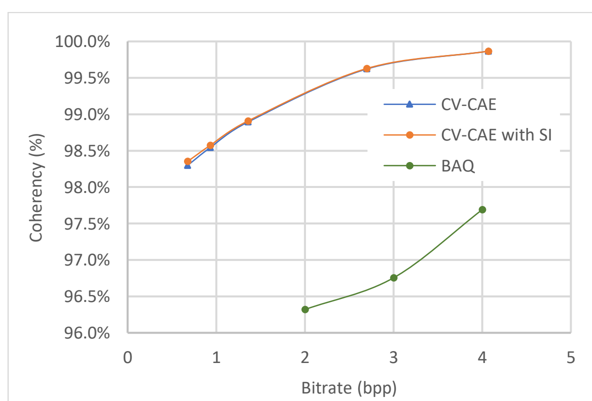

Fig. 3. The coherence between the original and the reconstructed SAR images for different compression rates with CV-CAE and BAQ.

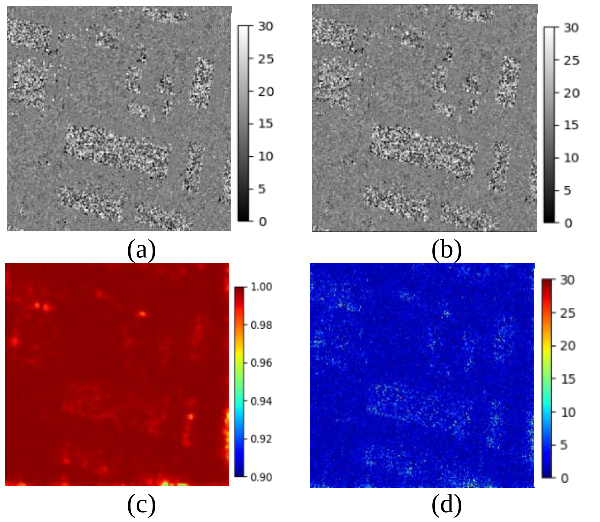

Fig. 4. (a) original amplitude, (b) reconstructed amplitude without side information, (c) coherence, and (d) phase error maps of a sample patch over industrial area. The dynamic range of the images are limited for better visualization.

4. CONCLUSION

The capability of the CV deep architectures for SLC SAR data compression is evaluated in this study. The obtained results demonstrate the remarkable potential of the CV networks to compress CV-SAR data. The CV autoencoder compresses the amplitude and phase components of the CV-SAR data together and demonstrates superior performance in comparison with the BAQ technique.

However, adding the side information from the other polarization channel of the SAR data to enhance the reconstruction of the compressed polarization channel, does not decrease the compression error. Further experiments and utilizing more advanced architectures for incorporating the side information and exploiting the correlation between the polarization channels of SAR data are necessary in order to achieve practically applicable networks with higher compression rates and less data loss and should be pursued in the future studies.

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