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Ph.D. THESIS SUMMARY

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DEEP LEARNING FOR SAR DATA IN PRESENCE OF ADVERSARIAL SAMPLES

ÎNVĂȚAREA PROFUNDĂ PENTRU DATE SAR ÎN PREZENȚA EȘANTINȚELOR ADVERSIALE

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Abstract

In the era of unprecedented climatic, geomorphologic, environmental, and anthropogenic changes in the Earth, a global-scale, long-term, and continues monitoring via Earth Observation (EO) sensors is imperative. Among EO sensors, Synthetic Aperture Radar (SAR) systems stand out due to their day and night observation capability and immunity to atmospheric conditions, and play an essential role in ensuring uninterrupted worldwide monitoring. However, SAR data have a high degree of complexity; they are Complex-Valued (CV) multidimensional signals with particular properties induced by the coherent imaging mode and the observed scene scattering process and the inherent adversarial effect.

Deep learning has emerged as a remarkably potent and widely adopted technique across diverse fields, showcasing its unparalleled effectiveness in tackling complex challenges, including remote sensing. This thesis is dedicated to explore novel deep learning-based solutions for SAR applications, considering unique characteristics of SAR data and capability of deep networks to learn and model data distribution of SAR data, to unveil new perspectives in this field. We delve into the CV deep architectures for this purpose to fully exploit the amplitude and phase components of SAR data. The research presented in this thesis can be classified into three parts:

In the first part, we investigate the Bayesian generative model, Latent Dirichlet Allocation, for big EO data mining of the semantic content and generate a CV semantically annotated dataset from Sentinel-1 (S1) Single Look Complex (SLC) StripMap (SM) mode products, called S1SLC_CVDL, for training CV deep networks.

Moving forward, the second part of the thesis is dedicated to the implementation of the CV networks and comprehensive analyses of these models, with respect to the particular characteristics of CV-SAR data. In this part, a wide range of operators, layers, and functions are converted into the complex domain for CV network's implementation. Later, extensive investigations are carried out on CV deep architectures for various SAR applications, illuminating the supremacy of CV models for semantic land cover classification, data distribution modelling, complex coherence preservation, and physical attributes interpretation and retrieval from SAR data.

Acknowledging their enormous potential, in the last part, we venture into the practical and more complicated applications of the CV networks. We employ CV networks to engineer a novel data compression approach utilizing CV autoencoders, tailored for compressing raw SAR data.

The demonstrated capabilities of the CV deep architectures in this thesis unravel new perspectives in the field of CV deep architectures for SAR applications and pave the way for the future development of physics-aware CV deep networks with data distribution modelling capability for various remote sensing applications.

Content

Chapter 1

Introduction

Deep learning models are the state-of-the-art data processing algorithms for most of the applications. However, it is important to carefully consider several factors while applying deep architectures for remote sensing applications, especially Synthetic Aperture Radar (SAR) data with peculiar properties. This chapter presents the motivation and main purpose of the thesis and summaries the main contribution to the field.

1.1 Overview

By capturing data in different wavelengths of the electromagnetic radiation, remote sensing and Earth Observation (EO) allow us to gather valuable insights about the Earth's features and enables global-scale monitoring of various phenomena. Among the EO sensors, the ability of SAR to acquire data almost independent of the weather condition and during day/night makes it an invaluable tool for monitoring various Earth processes. However, SAR data have a high degree of complexity, they are Complex-Valued (CV) multidimensional signals with particular properties and inherent adversarial effect induced by the coherent imaging mode and the observed scene scattering process. These particular peculiarities of SAR data introduce new challenges to interpreting and extracting semantically meaningful information from them.

Moreover, deep learning models have demonstrated the state-of-the-art performance and presented a major breakthrough and extremely powerful tool for many different tasks [1]. The immense advancements of deep learning models enabled the deep architectures to solve highly computational and complicated tasks and surpass other data processing and machine learning algorithms.

1.2 Motivation and Main Purpose

Witnessing the huge potential of deep architectures, and unprecedented increase in EO data availability, remote sensing researchers applied deep learning models to the EO data. However, remote sensing data are different from natural images and they would raise specific challenges for deep learning models. In the case of SAR data, one of the main issues is the employment of Real-Valued (RV) networks to the CV-SAR data. SAR data are in complex domain by nature and applying RV models will neglect the phase information, and only exploits the amplitude component of the CV-SAR data.

CV networks are developed to address this limitation of deep architectures. Despite the increased interests to develop novel CV networks for SAR data interpretation, and the immense advancements of the CV networks in the recent years, there are still several restricting factors that limit the broad advancement and employment of these models. The main motivation of this thesis is to address some the main challenges and provide solutions for better development of the CV deep architectures for SAR data processing and interpretation to address the gap for CV networks with ability to learn and model the complex data distribution of SAR data in presence of inherent adversarial samples. This study is aimed to take the CV deep networks beyond the simple analysis of CV signals and incorporate the physical properties of the SAR data into the CV models.

The main purpose of this thesis is to study the development of CV deep architectures for various SAR applications, provide solutions to address challenges, and to incorporate physics-aware and data distribution modelling attributes to the CV deep architectures to take them beyond just simply analyzing CV signals.

1.3 Main Contributions

The main contributions of this thesis are in the direction of the main purpose to study the data model learning ability of CV networks for SAR data in presence of adversarial samples, provide solutions based on CV deep architectures for various SAR applications and answering the abovementioned research questions. The main contributions of the thesis are summarized as follows:

- The necessary theoretical and mathematical background for implementation of the CV networks, including the CV operators, layers, and backpropagation algorithm are studied. The conversion of the operators from real domain to the complex domain are provided [2].
- The potential of data mining techniques, Bag of Visual Words (BOVW) and Latent Dirichlet Allocation (LDA) methods, for extracting semantically meaningful information from various EO data are explored [3], [4].
- The studied data mining techniques are employed and a large scale semantically annotated dataset from Sentinel-1 (S1) Single Look Complex (SLC) data for training CV Deep Learning models (CVDL) is developed and published open access on IEEE DataPort, called S1SLC_DL dataset, to pave the way for further research activities in the field of CV networks for SAR data [5].
- The importance of the capability of the CV networks for learning and modelling the data distribution of SAR data in presence of the inherent adversarial samples is discussed and competency of different data modelling techniques for this purpose is discussed [2], [6].

- The capability of the CV deep architectures to preserve the complex coherence of SAR data is evaluated. Comprehensive investigations are carried out to assess this capability, including the preservation of the subaperture property of SAR data [2], [7].
- Comprehensive analyses are carried out on the CV deep classification architectures as well as a thorough comparison between their classification performance with respect to the equivalent RV network and the state-of-the-art classification architectures and demonstrated the superiority of the CV networks in terms of higher classification accuracy, less training data, and lower computational cost [2], [8].
- The ability of the CV networks to learn the physical attributes and preserve the original basic properties of SAR data is evaluated for the first time. To this end, the effect of the CV networks on the Doppler centroid properties of SLC SAR data is assessed with regard to the ocean surface current estimation [9].
- Necessary concepts for data compression (e.g., rate-distortion theory, arithmetic encoding, and standard compression techniques) are studied for raw SAR data compression. To this end the performance of the well-known techniques, Block Adaptive Quantization (BAQ) and JPEG2000 techniques for raw SAR data compression in evaluated and compared [10].
- For the first time, a novel CV autoencoder architectures for neural compression of raw SAR data is developed. The rate-distortion curve resulted from the developed CV autoencoder-based compression scheme is evaluated in comparison with the well-known compression techniques, such as BAQ and JPEG2000, for raw SAR data. The superior performance of the CV autoencoder-based compression method demonstrated the potential of the CV networks for learning and understanding the SAR data model [6].

1.4 Thesis structure

Including the introductory chapter, this thesis contains six chapters. In summary, the thesis is structured as follows:

- Chapter 2 presents that theoretical background of the concepts used in this thesis.
- Chapter 3 introduces the EO data mining methods and the semantically annotated CV-SAR dataset developed in this study.
- Chapter 4 is devoted to the developed CV deep architectures for SAR data classification and reconstruction. Different properties of the developed CV networks are analyzed in this chapter.
- Chapter 5 takes the developed CV networks beyond the simple signal analysis domain and employs the CV deep architectures for raw SAR data compression.
- Chapter 6 concludes the findings and contributions of this thesis, as well as providing further research ideas and directions.

Chapter 2

Theoretical Background

This chapter provides an introduction to the basic concepts studied in this thesis. First in Section 2.1, the fundamentals of SAR data imagery are presented. Later, in Section 2.2 data modelling concept for complex SAR data distribution in presence of inherence adversarial samples is analyzed. Section 2.3 introduces the mathematical background for CV networks and the conversion of different operators including the convolutional, pooling, batch normalization, fully connected, different activation and loss functions, and backpropagation algorithm, from real to complex domain.

2.1 Fundamentals of Synthetic Aperture Radar (SAR)

RAdio Detection And Ranging (RADAR) is an active sensor that transmits radio (microwave) waves toward a target and receives the backscattered wave. Forward-looking radar (e.g., weather radar) cannot create images and the imaging radar has side-looking geometry. A slide-looking radar is usually carried on an airplane or an orbiting satellite and scans the Earth surface in two dimensions, range and azimuth.

The spatial resolution is defined as the minimum separation between the measurements that the sensor is able to discriminate. The spatial resolution of the created image is different in range and azimuth directions. The range resolution is proportional to the width of the transmitted pulses by the sensor, while the azimuth resolution is proportional to the width of the beam's footprint on the ground which itself is inversely proportional to the antenna length. As a result, a very large antenna is required to obtain reasonable azimuth resolution, which limits the azimuth resolution of the real aperture radar imaging systems [11]. Synthetic Aperture Radar (SAR) is an advanced signal processing algorithm to overcome this limitation. In SAR imaging system, the motion of the antenna along the azimuth direction is used to synthesize a larger effective antenna from a sequence of acquisitions made with a shorter moving antenna, which in turn leads to the images with a higher azimuth resolution [11].

SAR imagery systems are capable of acquiring data in day and night and almost in all weather conditions. These capabilities make the SAR systems a suitable mapping choice for many surveillance applications. Moreover, the interaction of the radar signals with the Earth surface is different from the other sensing systems and as a result can provide unique and attractive information.

However, interpreting SAR images is not straightforward. SAR observations have a high degree of complexity, they are Complex-Valued (CV) multidimensional signals with particular properties and inherent adversarial effect induced by the coherent imaging mode and the observed scene scattering process. The non-intuitive side-looking geometry of SAR imagery systems adds additional difficulty for interpreting SAR images, such as foreshortening, layover, and shadowing effect [11]. Additionally, the backscattered signal within a resolution cell in the SAR image is the coherent sum of several individual scattering events with different energy, and phase, which results in the grainy pattern in SAR images, known as speckle effect [12].

Moreover, the backscattered signal in SAR images contains both amplitude and phase components. To effectively utilize the phase information in SAR data, CV methods, such as CV deep networks are necessary. CV networks should be able to model the complex data distribution of SAR in presence of adversarial samples to effectively exploit the inherent relationships between the amplitude and phase, leading to improved performance in tasks such as SAR data classification and compression.

2.2 Data Modelling and Adversarial Samples

The main objective of this thesis is to provide solutions based on CV deep learning models, for various SAR applications, including classification and compression of CV SAR data and to address the gap for CV networks with ability to learn and model the complicated data distribution of SAR data. SLC and raw SAR data, have very high complexity and the ability of the deep models to effectively learn the complex data model is important to achieve efficient classification and compression performance.

Furthermore, adversarial samples pose a significant challenge for deep learning models. For instance, the various scattering mechanisms and also basic physical model as the influence of Doppler phenomena for moving targets can cause adversarial effect in SAR data [12]. Addressing the vulnerability of deep learning models to the inherent adversarial samples of SAR data is crucial for maintaining the reliability and accuracy of classification and the efficiency of data compression in SAR data applications.

Data models, such as latent variable models, are the foundation for the design of various machine learning algorithms. The main purpose of data models is understanding and representing the inherent structures within datasets. The power of machine learning algorithm lies in their ability to learn the data model of the training data and extract hidden structures and patterns. Furthermore, powerful generative models have demonstrated superior performance in classification and compression task of complex data. Many studies have investigated different generative models, including LDA, GAN, and autoencoders, for classification and compression tasks, and explored the effect of the adversarial samples on them.

In this section, two well-known data modelling techniques, autoregressive models and latent variable models are discussed, and later, three popular generative models are critically analyzed, regarding their ability to learn complex SAR data model, vulnerability against Adversarial samples, and compatibility with CV SAR data.

The choice between LDA, GANs, and autoencoders depends on the specific task, data type, and objectives. Autoencoders have demonstrated an immense potential for learning the complex data model of the training dataset and in this thesis, we focus on autoencoder architectures for classification and compression tasks due to their features such as flexibility for CV networks, complex distribution leaning ability, and generalizability.

2.3 Complex-Valued Networks

When the CV data occur naturally in a system, such as SAR imagery systems, the real and imaginary components are statistically correlated. While extending the RV operators into the complex domain, the preservation of this correlation between the real and imaginary components are necessary to properly utilize the CV data and extract the correct physical information from the SAR data [13].

All of the elements of the CV network, including the weight and bias kernels, different layers, and activation functions, are in the complex domain. However, loss function remains in the real domain to prevent empirical problems during the learning process [8], [14]. In this section of the thesis, comprehensively detailed explanations and equations of various CV operators are explained, including convolutional layer, pooling layer, batch normalization layer, fully connected layer, activation functions, loss functions, and backpropagation algorithm.

For instance, backpropagation is a Stochastic Gradient Descent (SGD) based method that is widely used for training deep learning models. The backpropagation algorithm minimizes the total error (loss) of the training samples in the training stage of the network by adjusting the weight and bias parameters of the network.

According to Liouville's theorem in complex analysis, a bounded holomorphic function must be constant on the entire complex distribution [14]. In other words, the loss and the activation functions of the CV model must be constant or unbounded. However, Wirtinger calculus [15] extended the complex derivation to non-holomorphic functions. Several articles utilized Wirtinger calculus to derive the CV backpropagation algorithm [14], [16]–[19]. A simplified version of the CV backpropagation based on the Wirtinger calculus, tailored for the case study of this thesis, is provided below.

According to the Wirtinger calculus, if z is a complex variable, $z = x + jy \in \mathbb{C}, (x, y) \in \mathbb{R}^2$, the partial derivatives of a complex function $f(z)$ with respect to z and $\bar{z}$ are as shown in (2.38):

$$\frac{\partial f}{\partial z} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} - j\frac{\partial f}{\partial y}\right), \quad \frac{\partial f}{\partial \bar{z}} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} + j\frac{\partial f}{\partial y}\right) \tag{2.38}$$

Later, the complex gradient can be defined as (2.39):

$$\nabla_z f = 2\frac{\partial f}{\partial \bar{z}} \tag{2.39}$$

Accordingly, the correction term for the weights of the lth layer $\Delta\omega_{ik}^{(l)}[t]$ can be computed as (2.40)

$$\Delta\omega_{ik}^{(l)} = \frac{\partial \mathcal{L}}{\partial \Re(\omega_{ik}^{(l)})} + j\frac{\partial \mathcal{L}}{\partial \Im(\omega_{ik}^{(l)})} \tag{2.40}$$

Loss $\mathcal{L}$ is not directly related to the weights $\omega_{ik}^{(l)}$ of the model and as a result, in order to compute the correction term for the weights in each layer, complex chain rule should be applied [20], [21].

$$\begin{aligned}\Delta\omega_{ik}^{(l)} = &\left(\frac{\partial \mathcal{L}}{\partial \Re(V_i^{(l)})}\frac{\partial \Re(V_i^{(l)})}{\partial \Re(\omega_{ik}^{(l)})} + \frac{\partial \mathcal{L}}{\partial \Im(V_i^{(l)})}\frac{\partial \Im(V_i^{(l)})}{\partial \Re(\omega_{ik}^{(l)})}\right) \\ &+ j\left(\frac{\partial \mathcal{L}}{\partial \Re(V_i^{(l)})}\frac{\partial \Re(V_i^{(l)})}{\partial \Im(\omega_{ik}^{(l)})} + \frac{\partial \mathcal{L}}{\partial \Im(V_i^{(l)})}\frac{\partial \Im(V_i^{(l)})}{\partial \Im(\omega_{ik}^{(l)})}\right)\end{aligned} \tag{2.41}$$

If the complex error term $\delta_i^{(l)}$ is defined as (2.42), (2.41) can be simplified as (2.43)

$$\delta_i^{(l)} = -\frac{\partial \mathcal{L}}{\partial \Re(V_i^{(l)})} - j\frac{\partial \mathcal{L}}{\partial \Im(V_i^{(l)})} \tag{2.42}$$

$$\Delta\omega_{ik}^{(l)} = -\delta_i^{(l)}\overline{O_i^{(l-1)}} \tag{2.43}$$

The error term $\delta_i^{(l)}$ has to be calculated in each layer to propagate the error and adjust the parameters of the model to obtain the desired outputs. The complex backpropagation algorithm backpropagates the error till the parameters (i.e., weights and biases) of the first layer of the deep network and adjusts these parameters concurrently according to the defined loss function.

Chapter 3

Big Earth Observation Mining for Semantic Information Discovery and S1SLC_CVDL Dataset Generation

Recent advances in remote sensing technology have provided (very) high spatial resolution EO data with abundant latent semantic information. This chapter focuses on the semantic information discovery methods, based on Bayesian generative models for data mining, such as Latent Dirichlet Allocation (LDA) and Bag of Visual Words (BOVW) models. Three different scenarios are used to evaluate the semantic information discovery in various remote sensing applications, including both optical and SAR data with different spatial resolutions. Moreover, a semantically annotated dataset from Sentinel-1 SLC data for CV deep learning applications, called S1SLC_CVDL dataset, is developed and introduced in this chapter.

3.1 Overview

In this chapter two well-known data mining techniques, LDA and BOVW models, are utilized for exploiting different EO data and extracting latent semantic information from them. LDA is a Bayesian generative probabilistic model which has been proposed by Blei et al. [22] for text modeling. In image domain, LDA models each image as a mixture of latent topics from a Dirichlet distribution. LDA uses BOVW representation of the image for this purpose and considers the visual words as topic representors to represent each image with a topic probability vector through a generative procedure.

The main objective of this chapter is to evaluate the capabilities of the data mining latent semantic analysis methods based on LDA and BOVW models for latent semantic information discovery in EO images with different scenarios. Therefore, three different scenarios with three different EO image datasets were employed for semantic information discovery of remote sensing images. As the first scenario, kernel-based BOVW and LDA are applied on very high resolution (30 cm) multispectral (3 RGB bands) EO image for semantic information discovery and enhancing the user-defined GT map in order to achieve a better and more semantically comprehensive classified map. Later, a similar procedure is employed with coarser spatial resolution (10 m) multispectral (3 RGB and 1 infrared bands) images to detect wildfire affected areas. And finally, in the last scenario, patch-based BOVW and LDA are employed on initially annotated SAR patches to detect misclassifications and errors in the initial classification results. The method developed in this scenario is utilized to develop a semantically annotated dataset from Sentinel-1 SLC data, called S1SLC_CVDL dataset.

3.2 Experimental Results

A summary of the third scenario and the S1SLC_CVDL dataset is provided here.

3.2.1 Scenario 3: Sentinel-1 patch-based annotation analysis and S1SLC_CVDL dataset development

Scarcity of the annotated remote sensing dataset and the difficulty of creating a high quality large-scale annotated EO dataset is an important and restricting factor in the development of various machine learning algorithms. Numerous datasets with diverse characteristics have been developed in the remote sensing literature for different applications, however, there is not a large-scale high-quality CV-SAR dataset. In order to tackle this problem, the LDA-based data mining technique is utilized in the third scenario of this chapter to develop a semantically annotated dataset from Sentinel-1 Single Look Complex (SLC) SM mode products for Complex-Valued Deep Learning (CVDL) networks (S1SLC_CVDL).

Three Sentinel-1 scenes over Chicago and Houston in the US, and Sao Paulo in Brazil are selected to include diverse urban areas as well as vegetation cover and water bodies. Abovementioned SAR scenes are divided into 289,760 non-overlapping patches of 100×100 pixels. Since the semantic annotation of the SAR patches are not available, 1274 patches are annotated manually, using the visual inspection via Google Earth Pro, in 7 semantic classes, including Agriculture (AG), Forest (woodland) (FR), High Density Urban Areas (HD), High Rise Buildings (HR), Low Density Urban Areas (LD), Industrial Regions (IR), and Water Regions (WR).

Later, SVM classifier, with histogram intersection kernel, is utilized to classify the SAR patches into the seven semantic classes, using the Gabor features. Several obvious classification errors are noticeable in the classified patches. In the next step, BOVW and LDA-based semantic analysis is used to identify and remove the classification errors and enhance the annotation of the patches.

As a result of the semantic analysis, number of the patches is reduced and the size of the dataset is decreased by about 5%. However, this procedure enhances the dataset in terms of less incorrectly classified patches, as well as less mixed patches consisting of multiple semantic classes. The overall accuracy is improved by about 2% and the average false positive rate is also decreased by about 2% for each class, after the semantic analysis. The developed S1SLC_CVDL annotated dataset is available at IEEE DataPort (http://ieee-dataport.org/11016) for research purposes [5].

3.3 Conclusion

Data mining-based semantic information discovery techniques including LDA and BOVW models are employed in this study with different remote sensing datasets to extract the latent semantic information from EO images for various applications.

Utilizing kernel-based BOVW representation and LDA topic model has enabled us to correct and enhance the user-defined GT map and identify the neglected semantic classes in very high resolution (0.3 m) USGS aerial imagery with RGB optical bands. The corrected GT map resulted in a more semantically meaningful and comprehensive classified map, as well as less misclassification errors.

Additionally, RGB and NIR spectral bands of the Sentinel-2 optical imagery with coarser spatial resolution (10 m) are used to detect the affected areas in the wildfire, a few days and several months after the incident. The results demonstrated the capability of the semantic discovery method to detect various phenomena (e.g., wildfire affected area) in EO optical imagery. Additionally, this scenario demonstrated the capability of the data mining semantic analysis to detect the relevant spectral bands with more informative data for the target application.

Furthermore, BOVW and LDA-based data mining technique is used to develop a semantically annotated dataset from Sentinel-1 SLC data for complex-valued deep learning model (S1SCL_CVDL dataset). For this purpose, three scenes from the Sentinel-1 SAR imagery with SM imaging mode are divided into 100×100-pixel patches and a few patches are annotated manually into 7 semantic classes via visual inspection and Google Earth images. Gabor texture features and the well-known SVM classifier are used for the initial annotation of the patches. Later, the data mining semantic information discovery method is utilized to clean the annotated dataset and remove the misclassified patches, as well as removing the patches with ambiguous or multiple semantic labels.

The experiments carried out in this chapter, demonstrated the immense capabilities of semantic data mining techniques for various remote sensing contexts. However, more inspections are necessary to evaluate the competence of the semantic analysis methods in future studies.

Chapter 4

Complex-Valued Deep Architectures for SAR Data with Coherence and Original Properties Preservation

In this chapter, the performance of the CV deep architectures for various SAR applications is studied. Three different CV architectures, including a CV end-to-end deep network with two classification and reconstruction output heads, a CV Convolutional Autoencoder (CAE) and a CV Convolutional Neural Network (CNN), are developed for the reconstruction and classification of CV-SAR data. Several experiments are carried out to examine and showcase the potential of the CV networks for different SAR applications.

4.1 Overview

Despite the recent interests and developments in CV deep models for SAR data processing, there are several restricting factors that have limited the broad advancement of these models. In this chapter, the CV operators, defined in Chapter 2, are utilized to implement CV deep architectures and several analyses are carried out to investigate the performance and potential of the CV architectures for different SAR applications and address some of the limitations. An end-to-end architecture with classification and reconstruction heads, as well as two more specific architectures for specifically classification and reconstruction of SAR data are designed and implemented. The CV deep architectures are used to explore the performance and proficiency of the CV networks for various SAR applications, in 6 case studies.

The S1SLC_CVDL dataset, developed in introduced in Chapter 3, is used in this chapter for training and testing the CV networks. Moreover, a PolSAR image, acquired by the NASA/JPL AirSAR system over an agricultural area in the Flevoland, Netherlands with the size of 750×1024 is used to evaluate the classification performance of the CV models for PolSAR data. Furthermore, a Sentinel-1 scene acquired in interferometric wide-swath (IW) mode over Mamaia beach, in the Romanian coast of the Black Sea, is used to explore the capability of the CV networks to preserve the original properties of SAR data.

4.2 Experimental Results

In this section, the developed CV architectures are utilized in different case studies to investigate various aspects of the CV deep architectures for SAR applications.

4.2.1 Case study 1, CV-SAR classification with end-to-end architecture:

In this case study, the end-to-end architecture is used to classify the CV-SAR data from S1SLC_CVDL dataset. Orange Color charts in Figure 4.5 demonstrate the overall and class-based classification accuracies obtained from the proposed CV end-to-end model for this case study. The CV end-to-end deep network obtained about 90.7% overall classification accuracy. The lowest accuracies are obtained in the constructed classes where the LD class is classified with only 43.85% accuracy. However, in the three-class scenario, the constructed classes are separated with high accuracy and the most important confusion is between the different types of the constructed semantic classes. The main reason for the very low classification accuracy of the LD class is the confusion between this class and the other constructed classes, especially industrial fields. The other three constructed classes, HD, HR, and IR semantic classes, are classified with almost similar classification accuracies, around 78%.

In conclusion, despite the confusion between different constructed classes, the proposed CV end-to-end deep network successfully classified the challenging S1SLC_CVDL dataset with reasonable accuracy and utilized the amplitude and phase information of the CV-SAR images.

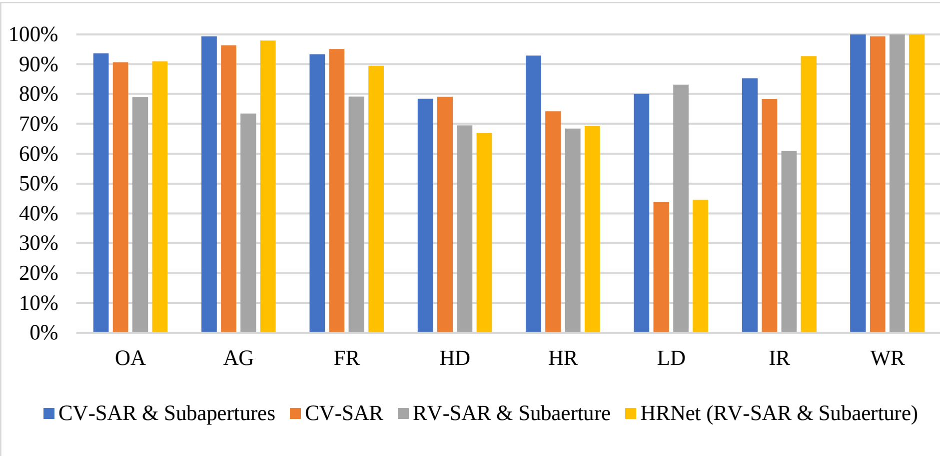

Figure 4.5 *Classification accuracies for the seven-class semantic annotations in different case studies.*

4.2.2 Case study 2, CV end-to-end architecture with incorporated physics-aware attributes:

In this case study, three overlapping (20%) subaperture images are extracted from each polarization channel of the CV-SAR patches of the S1SLC_CVDL dataset (i.e., Six CV subaperture images for each patch). Fourier Transform can be used to derive the subaperture images from pre-processed SAR data. It should be noted that the obtained subaperture images are also in the complex domain. While using the azimuth subaperture decomposition, one should consider that the subaperture images will have proportionally lower resolution, as we are using only a portion of the full available system bandwidth [23]. In addition, Zero Doppler for the moving targets, including trains or cars, might be in different positions which increases the possibility of defocused targets and miss detection [23].

The CV subaperture images (six channels, three from each polarization channel), along with the CV-SAR images (two channels) are fed into the proposed CV end-to-end deep model and the classification results are reported with the blue color charts in Figure 4.5. The overall accuracy increased about 3% in comparison to the previous case study and reached 93.72%. the most apparent improvement is in the LD semantic class. LD class is classified with more than 80% accuracy, which is almost two times more than the classification accuracy of this class in the previous case study. However, the confusion between different constructed semantic classes is still a challenge. The most problematic confusion in this case study is between the HD and HR semantic classes.

In conclusion, adding the CV azimuth subaperture images has enabled the proposed CV end-to-end deep architecture to better classify different constructed semantic classes. The physics-aware attribute of the deep model improved the classification results significantly, especially in the constructed areas. As shown in the Chapter 3, the S1SLC_CVDL dataset is very challenging and contains very similar targets, especially in constructed classes. However, the proposed CV end-to-end deep model is successful to classify the challenging dataset and exploit the valuable information in both amplitude and phase components of the CV-SAR images, as well as the physical properties in the CV azimuth subaperture images.

4.2.3 Case study 3, CV vs. RV networks:

In order to evaluate the effect of the CV networks on the classification results, two architectures are compared in RV and CV formats, end-to-end architecture for S1SLC_CVDL dataset and CNN architecture for PolSAR data classification.

End-to-end architecture:

In the first experiment, an equivalent RV end-to-end deep network is designed. Similar to the previous case study, 8 input channels are used in this case study. The amplitude of the SAR and the subaperture images used in the RV network and the classification results are reported with the gray color charts in Figure 4.5. The RV equivalent network with RV-SAR and RV-subaperture images obtained 79.01% overall classification accuracy.

The CV end-to-end network achieved higher classification accuracy for all of the classes, when the same input images (SAR and azimuth subaperture images) are used. The better performance of the CV network demonstrates the superiority of this network. The CV model is able to exploit more valuable and distinctive information from both the amplitude and phase components of the SAR data.

In conclusion, the CV deep end-to-end network achieved about 14% higher overall classification accuracy with the same input data. Only in the LD class, the RV network achieved slightly higher classification accuracy. However, the very high false-positive rate of this class in the RV model explains the higher accuracy and demonstrates the poor performance of the RV network despite the higher accuracy for this class.

CNN Architecture:

In the second experiment of this case study, the CV and RV CNN architectures are used to classify PolSAR data. The three RV and three CV elements of the upper triangle of the covariance matrix are used as the input features of the models. In order to preserve the equivalency between the networks, the same architecture is used for the CV-CNN and RV-CNN.

The performance of the CV-CNN and RV-CNN are compared in terms of the model convergence with different trainset sizes, classification accuracy, and the computational efficiency of the models.

In order to compare the convergence rate of the models, the size of the trainset is changed between 5% and 50% of the GT and the models are trained with 100 epochs. The test accuracy of the CV model with only 5% trainset size reaches about 92% and 94% after 50 and 100 epochs, respectively. However, the RV model needed at least 30% trainset size for the similar performance. CV-CNN has a remarkable testing accuracy of more than 98% with 50% trainset size.

In terms of classification accuracy, with 10% trainset size, the CV-CNN and RV-CNN models achieved more than 95% and 90% Overall Accuracies (OA) for the test set, respectively. Only in two classes, Forest and Bare soil, the RV model achieved higher classification accuracies, however, the accuracy of the CV-CNN is remarkably higher in other 13 semantic classes.

Despite the superior performance, CV-CNN has two times more trainable parameters than RV-CNN, 39,034 and 19,517 parameters, respectively, and as a result the training time is much higher for the CV model. However, CV model reaches higher OA with less training epochs. For instance, for the target OA of more than 90%, CV model needs 17 epochs and 173.32 seconds training time, while the RV model needs 39 epochs and 192.26 seconds training time.

In conclusion, using the phase component of PolSAR data in CV deep architectures can boost the classification results, and will require smaller trainset and less training epochs and time.

4.2.4 Case study 4, CV end-to-end vs. RV HRNet:

The architectures used in this chapter are simple and basic convolutional networks and they can be improved to achieve better results. Many different architectures have been proposed in the literature to improve the performance of the deep networks, including High-Resolution Network (HRNet). In this case study, CV end-to-end network with the same architecture, is compared with the RV HRNet. Similar to the previous case study, 8 input channels, consisting of two SAR polarization channels and six subaperture images, are used (i.e., in complex domain for the CV network and in real domain for the RV HRNet).

The HRNet obtained 90.97% overall accuracy, which is almost 3% lower than the CV network. The CV network achieved higher classification accuracy for all of the classes, except for the IR class. Although, the false positive rate of this class is very high, mostly as a result of the confusion between this class and HD and LD classes. However, the RV HRNet obtained remarkably better performance than the RV network with the end-to-end architecture in. The input for both of these networks is the same (8 RV channels), but the HRNet obtained almost 12% higher overall classification accuracy.

The results of this case study, demonstrated that the HRNet has a better architecture than the end-to-end network, but the CV operators achieved higher classification accuracy even with a shallower and weaker architecture. It should also be noted that HRNet has more trainable parameters than the CV network (HRNet has 21,301,884 parameters and the CV network has 18,466,186 parameters).

4.2.5 Case study 5, coherence preservation capability:

In SAR imagery, the complex correlation coefficient (Coherence) contains important information about the SAR system and the physical properties of the target [24]. As a result, the coherence of CV-SAR data must be preserved in the processing chain and a fully CV network with a coherence preservation feature is necessary. Processing the amplitude and phase components (or the real and imaginary parts) of the CV-SAR data separately will interrupt the coherence of CV-SAR data. Although CV deep networks can be beneficial to preserve this coherence and exploit the phase information [14], the coherence preservation capability of the developed CV networks should be evaluated and monitored to ensure the coherence preservation. In this case study, two CV networks are used to evaluate the coherence preservation capability of the CV networks, CV deep end-to-end network and CV CAE model.

CV deep end-to-end architecture:

The CV end-to-end network is used with the 8 CV input channels consisting of two CV-SAR and six CV subaperture images. In the first step, the correlation between the reconstructed CV-SAR image by the CV-CAE and the input image is assessed. The average coherence between the input and the reconstructed CV-SAR patches is 0.9415. The high coherence demonstrates the preservation of the complex correlation coefficient of the CV-SAR patches in the CV deep model.

Furthermore, the developed CV deep network should learn the CV data model in a way that different apertures in the reconstructed CV-SAR image still represent the different antenna angles. In order to evaluate the developed CV end-to-end deep model for learning and preserving the CV data model, the subaperture decomposition is also applied to the reconstructed CV-SAR patches. The average coherence of 0.9214 between the subaperture images demonstrates the capability of the developed CV deep model to learn and preserve the data model.

CV CAE architecture:

Additionally, the CV CAE architecture is utilized in this case study to assess the preservation of the complex coherence in CV-SAR image reconstruction. For this purpose, similar 8 CV input channels as the end-to-end architectures are fed into the CV CAE network and the coherence between the input and the reconstructed SAR patches, and the subaperture images from the original and the reconstructed SAR patches are evaluated. The high coherence value demonstrated the capability of the CV CAE model to learn the data model and preserve the complex coherence.

4.2.6 Case study 6, maintaining the Doppler centroid and original properties of SAR data:

SAR images convey the physical attributes and information of the observed target and if the physical data model and basic properties of the original SAR data is maintained during the processing chain, the physical parameters of the observed target can be accurately retrieved from SAR data. For instance, the phase information in SLC SAR images can be used to retrieve physical information about the Ocean Surface Current (OSC) from EO data. CV deep networks, due to their ability to process the phase information and also, as shown in the previous case study, their proficiency to learn and preserve the data model and complex coherence of CV-SAR data, are suitable algorithms for this purpose. However, the ability of the CV networks for maintaining the basic properties of the original SAR image, Doppler centroid in this case, should be evaluated.

To this end, the CV end-to-end network is utilized, disregarding the classification output head. Subsequently, the ocean circulation parameters were estimated from the SAR data before and after reconstruction using the CV autoencoder, and the results were compared. Sentinel-1 IW mode data acquired over the Mamaia beach in the Romanian coast of the Black Sea is used in this case study.

The Correlation Doppler Estimation (CDE) method [25] and the Radial Surface Velocity (RSV) [26] are used to extract the Doppler information and estimate the OSC from them. The CV autoencoder is trained once with the S1SLC_CVDL data (SM mode, HH-HV polarization) and another time is retrained with the data from this case study (IW mode, VV-VH polarization). The results from these two networks are annotated with “R” and “RT”, respectively. In order to assess the impact of the CV network on the ocean surface parameters’ estimation, the OSC is estimated from the original SAR data before the CV network, annotated with “O”, and also with the “R” and “RT” networks.

Comparing the f_{DC} and OSC estimated from the “R” network with the original SAR data, a noticeable difference in the estimated ocean circulation parameter is visible. The reconstructed CV-SAR data, despite having a similar OSC pattern, tends to estimate lower values for the current and weaker Doppler. However, when the CV autoencoder is retrained using the IW data, the estimated f_{DC} and OSC show a very high resemblance with the results from the original SAR data. The high resemblance between the ocean circulation parameter's estimation in the original and the reconstructed SAR data demonstrates that the CV autoencoder has preserved the SAR data model even without retraining (experiment annotated with R). Obviously, retraining the network with a similar type of data (IW and VV-VH Polarization channels) has improved the performance of the CV autoencoder significantly.

When we compare $OSC^{(O)}$ with $OSC^{(R)}$, we get a Root Mean Square Error (RMSE) of 0.26, a correlation of 0.85, and a Mean Absolute Error (MAE) of 0.14. Nevertheless, when we compare $OSC^{(O)}$ and $OSC^{(RT)}$, there is a good agreement with a smaller RMSE of 0.11, a strong spatial correlation of 0.97, and an insignificant MAE of 0.05, which is also evident from the slope of the regression line for both comparisons.

In conclusion, the immense potential of CV deep architectures for physical parameter retrieval and prediction, owing to their ability to preserve the original SAR data properties, is demonstrated in this case study.

4.3 Conclusion

In this chapter, CV deep networks are employed for CV-SAR data reconstruction and classification and addressed a number of the shortcomings of the previous CV models for SAR data processing. Three CV deep architectures, including a deep end-to-end architecture with two classification and reconstruction heads, a CNN, and a CAE models, are designed and implemented in different case studies to evaluate various aspects of the proficiency of the CV networks for SAR applications. Six different case studies are defined and the proficiency of the CV networks in these case studies is assessed. The findings of this chapter demonstrate the immense potential of CV networks for various SAR applications and unveil new perspective in this field for the future studies.

Chapter 5

Synthetic Aperture Radar Data Compression

The improvements of the advanced SAR system capabilities imply also 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 SAR satellites and directly affects the quality of the generated SAR image. Neural compression techniques using deep models have attracted many interests for natural image compression tasks and demonstrated promising results. Witnessing the immense potential of the CV networks for SAR applications, in this chapter, we delve into a more practical application of the CV networks by employing them for raw SAR data neural compression.

5.1 Overview

Particular peculiarities and characteristics of SAR data such as CV nature, large dynamic range, inherent speckle effect, and the spatial correlation necessitate the development of novel compression methods for compressing raw SAR data, considering its unique characteristics. These features make conventional image compression techniques not very convenient.

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 [27]–[29]. Bearing in mind the huge potential and high proficiency of the CV deep architecture for various SAR applications, explored in the previous chapter, in this chapter, the compression of the CV raw SAR data is inspected. Due to the unavailability of the uncompressed Senmtinel-1 raw SAR data, a novel method is proposed to add random uniform quantization noise to the FDBAQ-compressed raw data in order to generate uncompressed raw SAR data with quasi-uniform quantization. Later, a CV autoencoder-based compression scheme is developed for SAR data neural compression. The developed network is evaluated for raw SAR data compression with uniform quantization and the results are compared with well-known compression methods, BAQ and JPEG2000.

5.2 Quasi-uniformly Quantized Raw SAR Data Generation

As a result of the unavailability of the uncompressed raw Sentinel-1 data, we generated quasi-uniformly quantized raw data by adding quantization noise to the FDBAQ compressed raw SAR data. In this way, we would have the original samples on the right number of bits. The experiment has been carried out on the three Sentinel-1 scenes, acquired over Chicago, Houston, and Sao Paulo (i.e., the same scenes as the S1SLC_CVDL dataset).

The defined procedure results in the data with 256 quantization levels. Figure 5.7 illustrates the quantization steps of the decoded data before (blue) and after (red) adding the uniform noise, note the horizontal axis (0-255 for the red plot).

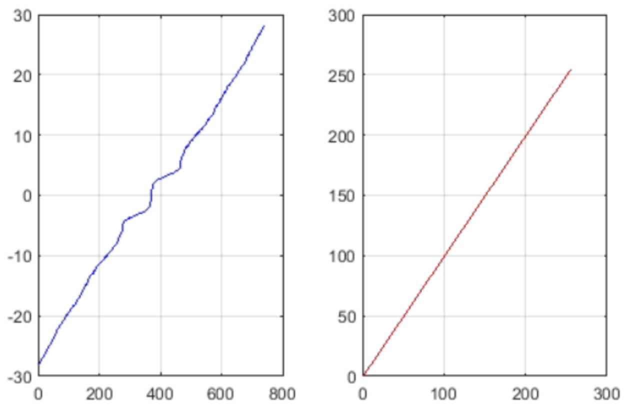

Figure 5.7 *Quantization steps in the decoded data, before (blue) and after (red) adding the uniform noise. Note the horizontal axis (0-255 for the red plot).*

In order to evaluate the proposed methodology and how it affects the compression methods, JPEG2000 compression algorithm with different compression rates is applied to the data before and after adding the quantization noise. It should be noted that the JPEG2000 algorithm can only be applied to RV data. As a result, JPEG2000 is applied to the real and imaginary components of the decoded raw data, separately. Later the decompressed data is processed to obtain the SLC images and compute the Signal to Quantization Noise Ratio (SQNR).

The results demonstrate that the added quantization noise did not distort the data and the obtained SLC images after adding the quantization noise have high quality. Moreover, adding the quantization noise did not disrupt the performance of the JPEG2000 compression method. These results show the effectiveness of the method to have the raw data samples on the right number of bits and not affecting the performance of the compression method.

5.3 Raw SAR Data Compression

A CV deep network, based on the autoencoder architectures is used for neural compression of raw SAR data. The architecture of the proposed model consists of three main parts, encoder, entropy model, and decoder. Figure 5.3 shows the architecture of the proposed autoencoder-based 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. Moreover, all of 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.

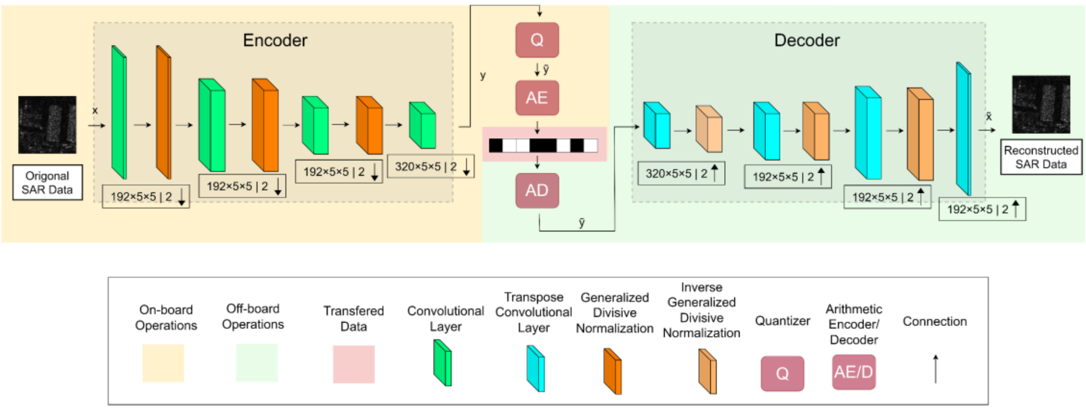

Figure 5.3 *Architecture of the proposed autoencoder-based compression model. In this figure, below each convolutional or transpose convolutional layer, a box is showing "number of filters" × "kernel height" × "kernel width" | "stride size". In these boxes, downward arrows show downsampling in the convolutional layers and the upward arrows show upsampling in the transpose convolutional layers. Moreover, all of 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 presented method in section 5.2 is used to preprocess raw SAR data and apply the compression methods. The BAQ, JPEG2000, and CV autoencoder-based compression methods are applied to the raw data. In should be noted that the JPEG2000 is applied separately to the real and imaginary components of the CV raw SAR data. The compressed/decompressed data are processed to obtain the SLC SAR images and the evaluation metrics are measured between the SLC SAR images before and after compression.

Three different measures, including SQNR, phase error and complex coherence, are measured between the resulted SLC images before and after compression/decompression of the raw data with the BAQ, JPEG2000, and CV autoencoder-based compression methods. Figure 5.12 shows the SQNR comparison.

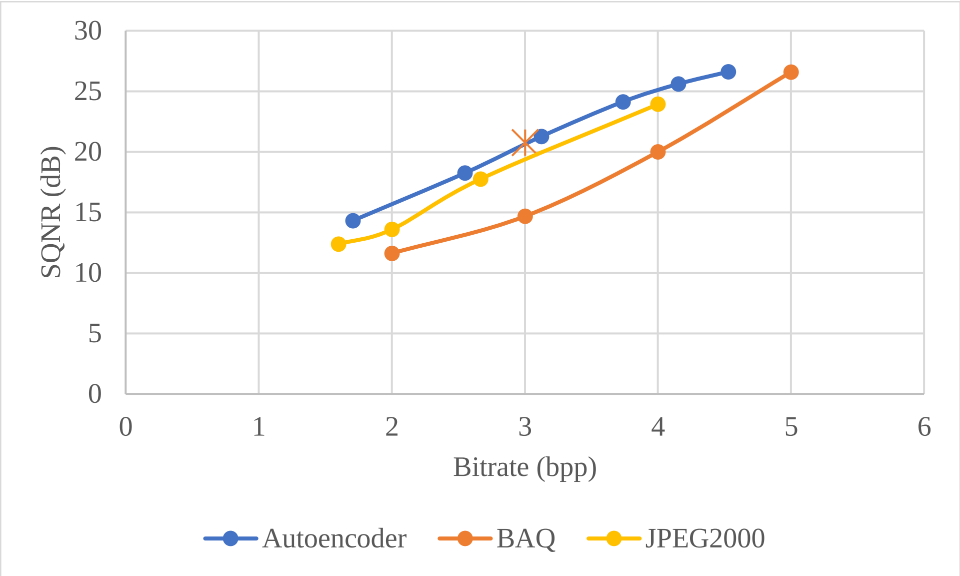

Figure 5.12 *Comparative analysis of the CV autoencoder, BAQ, and JPEG200 compression with SQNR metric. The orange × shows the unexpected behavior of BAQ with 3 bpp as explained above.*

The obtained results demonstrate the superior performance of the CV autoencoder-based compression scheme for raw SAR data compression, with respect to the BAQ and JPEG2000. The CV autoencoder obtained about 4-6 dB higher SQNR than BAQ and about 1-2 dB higher than JPEG2000. The superior performance of the CV autoencoder is evident also in the phase error and coherence metrices.

5.4 Conclusion

SAR raw data compression problem is explored in this chapter. Neural data compression methods, based on deep architectures are extended to the complex domain and a CV autoencoder-based compression scheme is designed. Moreover, BAQ and JPEG2000 methods are employed for SAR data compression. In conclusion, the findings of this chapter demonstrated the competency and potential of the CV deep architectures for raw SAR data compression. CV architectures are competent to handle raw SAR 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.

Chapter 6

Conclusions

The main purpose of this thesis is to provide CV deep learning-based solutions for complex SAR data with the ability to learn the distribution of SAR data in presence of adversarial samples, investigate characteristics of the CV networks for complex coherence and data model preservation, and incorporating physics-aware attributes to the models. To this end in this thesis, we explore the CV deep architectures, their implementation and the challenges and considerations regarding employing these networks for various SAR applications.

6.1 Main Contributions of the Thesis

To put it all together, the main contributions of this thesis in the field can be summarized as the following:

- Due to the complex distribution model of SAR data, CV networks should be able to learn and model the data distribution of SAR data in presence of the inherent adversarial samples. This capability of CV networks is discussed and competency of different data modelling techniques for this purpose is analyzed.
- The CV networks and essential operators for their implementation are thoroughly examined, offering a comprehensive explanation of various operators and layers within the CV deep architectures.
- Big EO data mining of semantic content using Bayesian generative model, the Latent Dirichlet Allocation, is explored for a variety of remote sensing applications.
- The LDA-based data mining technique is employed to generate S1SLC_CVDL dataset, the first SAR large-scale semantically annotated dataset from Sentinel-1 (S1) SLC data for training CV Deep Learning (CVDL) models.
- Comprehensive analyses are carried out on the CV networks and their competency for SAR data applications in different aspects are examined:
    - The classification performance of the CV is compared with the equivalent RV architecture, as well as with a state-of-the-art classification architecture, HRNet. These comparisons show that the CV

network achieves higher classification accuracy with less training samples, and shallower architectures (i.e., lower computational cost).
  - Physical attributes from SAR data are incorporated with the CV models and illustrated the feasibility of physics-aware CV architectures.
  - For the first time, the ability of the CV networks for learning the modelling data distribution of SAR data in presence of inherent adversarial samples and preserving the complex coherence of SAR data is examined.
  - For the first time, the CV networks are explored for learning the physical data model of SAR data and preserving the Doppler centroid information and original properties of SAR data. This capability of CV architectures is examined with regard to the ocean surface current estimation and demonstrated the potential of these networks for interpreting physical information of SAR data.
- Necessary concepts for raw SAR data compression (e.g., rate-distortion theory, arithmetic encoding, and standard compression techniques) are studied. Feasibility of the well-known JPEG2000 algorithm for raw SAR data compression is explored and showcased a superior performance with respect to the BAQ technique.
- Finally, for the first time, the concept of neural data compression is evaluated for raw SAR data compression. Raw SAR data have peculiar attributes and the compression model should be able to preserve them for focusing and obtaining the SAR image. A CV autoencoder-based compression scheme is designed and implemented for this purpose and demonstrated remarkable potential of CV networks for this purpose.

6.2 List of Publications

6.2.1 Journal Articles

1. R. M. Asiyabi and M. Datcu, “Earth Observation Semantic Data Mining: Latent Dirichlet Allocation-based Approach,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, J-STARS, vol. 15, pp. 2607-2620, 2022, doi: 10.1109/JSTARS.2022.3159277.

2. R. M. 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 Transactions on Geoscience and Remote Sensing, TGRS, vol. 61, pp. 1-17, 2023, Art no. 5206417, doi: 10.1109/TGRS.2023.3267185.

3. R. M. Asiyabi, M. Datcu, and A. Anghel, “Complex-valued autoencoder-based compression scheme for SAR raw data,” To be Submitted, 2023.

6.2.2 Conference Proceedings

1. R. M. Asiyabi and M. Datcu, "Earth Observation Image Semantics: Latent Dirichlet Allocation Based Information Discovery," in IGARSS 2021 - IEEE International Geoscience and Remote Sensing Symposium, Brussels, Belgium, 2021, pp. 2620-2623, doi: 10.1109/IGARSS47720.2021.9553122.

2. R. M. Asiyabi, M. Datcu, H. Nies and A. Anghel, "Complex-Valued Vs. Real-Valued Convolutional Neural Network for PolSAR Data Classification," in IGARSS 2022 - IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 2022, pp. 421-424, doi: 10.1109/IGARSS46834.2022.9884081.

3. R. M. Asiyabi, M. Datcu, A. Anghel and H. Nies, "Complex-Valued Autoencoders with Coherence Preservation for SAR," in EUSAR 2022; 14th European Conference on Synthetic Aperture Radar, Leipzig, Germany, 2022, pp. 1-6.

4. R. M. Asiyabi, A. Anghel, P. Rizzoli, M. Martone, and M. Datcu, “Complex-Valued Autoencoder for Multi-Polarization SLC SAR Data Compression with Side Information,” in IGARSS 2023 - IEEE International Geoscience and Remote Sensing Symposium, Pasadena, United States, 2023, pp. 1787–1790.

5. M. A. Iqbal, R. M. 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 CBMI 2023 - 20th International Conference on Content-based Multimedia Indexing, Orleans, France, 2023.

6. R. M. Asiyabi, A. Anghel, A. Focsa, M. Datcu, M. Martone, P. Rizzoli, and E. Imbembo, “On the use of JPEG2000 for SAR raw data compression,” Submitted to the European Conference on Synthetic Aperture Radar, EUSAR, 2024.

6.2.3 Datasets

1. R. M. Asiyabi, M. Datcu, A. Anghel, H. Nies, April 8, 2023, "S1SLC_CVDL: A Complex-Valued Annotated Single Look Complex Sentinel-1 SAR dataset for Complex-Valued Deep Networks", IEEE DataPort, doi: https://dx.doi.org/10.21227/nm4g-yd98.

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