COMPLEX-VALUED NEURAL NETWORKS FOR POLARIMETRIC SAR SEGMENTATION USING PAULI REPRESENTATION

J. A. Barrachina[⋆†] *C. Ren*[⋆] *C. Morisseau*[†] *G. Vieillard*[†] *J.-P. Ovarlez* [⋆†]

[⋆] SONDRA, CentraleSupélec, Université Paris-Saclay, 91192 Gif-sur-Yvette, France
[†] DEMR, ONERA, Université Paris-Saclay, 91120 Palaiseau, France

ABSTRACT

In the context of a growing popularity of Complex-Valued Neural Network (CVNN) for Polarimetric Synthetic Aperture Radar (PolSAR) applications, the input features often play a central role in classification and segmentation tasks. The so-called coherency matrix, widely used in the radar community, might limit the full potential of CVNNs. Particularly, complex-valued Pauli representation contains richer information than the coherency matrix. And the spatial coherent/local summation can also be performed by the first convolutional layers of CVNN. Letting this network learn itself the filters weights will further enhance its performance.

In this paper, we propose a Complex-Valued Fully Convolutional Neural Network (CV-FCNN) which directly infers on the Pauli vector representation rather than on the coherency matrix to perform PolSAR image segmentation. The performance of CV-FCNN is then statistically evaluated on Bretigny PolSAR dataset and compared against an equivalent real-valued model.

***Index Terms*—** Polarimetric Synthetic Aperture Radar, Complex-Valued Neural Network, Complex-Valued Fully Convolutional Neural Network, Pauli representation.

1. INTRODUCTION

Deep learning techniques are becoming widely popular and have extended into Polarimetric Synthetic Aperture Radar (PolSAR) image classification [1, 2]. In particular, numerous publications occurred using Complex-Valued Neural Network (CVNN) as an alternative to conventional Real-Valued Neural Network (RVNN) for radar applications [3, 4].

One of the first works on classifying PolSAR images using deep learning was implemented by reference [5] who used a Complex-Valued MultiLayer Perceptron (CV-MLP) as well as [6]. Numerous articles thereafter proposed a Complex-Valued Convolutional Neural Network (CV-CNN) for performing PolSAR classification [7–10]. However, PolSAR applications are better suited for semantic segmentation analysis as multiple class are present in a single SAR acquisition. This makes networks such as Complex-Valued Fully Convolutional Neural Network (CV-FCNN) better suited for the task at hand. Indeed [11] and [12] obtained a state-of-the-art performing utilizing such networks.

Most works mentioned above use at least one of the three well-known open-source datasets of San Francisco, USA [13]; Flevoland, Netherlands and Oberpfaffenhofen, Germany, provided by the European Space Agency (ESA). These datasets are presented in the form of the Hermitian coherency matrix. Even though the coherency matrix is a well-known and popular representation of data for PolSAR applications, it might not be well suited for complex pixel-wise segmentation tasks as explained on section 2.

Using another PolSAR dataset, we propose to train the CVNN network using Pauli representation as input, which has, so far, not been used for CVNN. We qualitatively analyze the pros of this format. For this work, we split the dataset into train, validation and test sets that prevents the overlapping of labels and makes training and test pixels farther apart. We then compare the performance of CVNN against an equivalent RVNN for this given input format.

Section 2 presents the dataset and its pre-processing. Section 3 shows the model architectures used for the experiments. Finally, section 4 analyzes and compares the performance of the proposed neural network.

2. DATASET AND INPUT FEATURES

PolSAR makes use of signal coherence (or equivalently phase and local phase variance) existing on any single look complex data channels S measured in the horizontal (H) and vertical (V) transmit/receive polarimetric channels $S = \left[S_{HH}, \sqrt{2}\, S_{HV}, S_{VV}\right]^T$.

For each pixel of the Synthetic Aperture Radar (SAR) image, this backscattering vectors are usually expressed in the Pauli basis and are vectorized onto one single complex vector $\boldsymbol{k} = 2^{-1/2}\left[S_{HH} + S_{VV}, S_{HH} - S_{VV}, 2\, S_{HV}\right]^T \in \mathbb{C}^3$ [14]. The Hermitian coherency matrix is formally built according to $\boldsymbol{T} = \frac{1}{n}\sum_j^n \boldsymbol{k}_j\, \boldsymbol{k}_j^H$ where the operator ^{H} stands for complex conjugate operation and where n is the number of pixels chosen in a boxcar located in each local area.

Open-source PolSAR datasets are usually presented in the

The authors would like to thank the Délégation Générale de l'Armement (DGA) for funding.

coherency matrix form $\mathbf{T}$ [13]. This representation may not be the optimal representation for CVNN applications for several reasons. First, the diagonal elements of this matrix are real-valued, that although being a valuable property for many applications, it is not desirable for CVNN. Second, the averaging operation, whose main objective is to reduce noise at the expense of losing information or resolution, mixes values of adjacent pixels rendering it difficult for pixel-wise classification. Additionally, the averaging algorithm is a non-trainable convolution operation with a constant kernel. Letting these kernels be trainable generally enhances the performance of classification and segmentation. Therefore, the Pauli vector $\boldsymbol{k}$ is chosen as input for our CV-FCNN which implies that each pixel of the PolSAR image will be represented by three complex values.

Unfortunately, extracting the Pauli vector from the coherency matrix is impossible, making not exploitable the open-source datasets from ESA mentioned previously. We, therefore, use an ONERA's proprietary PolSAR image of Bretigny, France [15] whose area is shown in Figure 1.

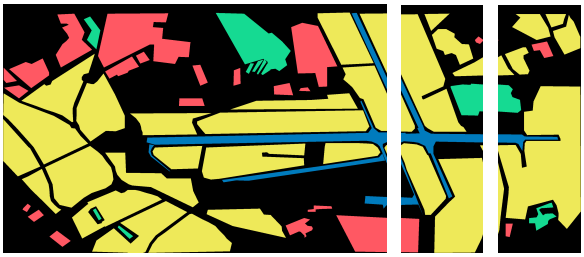
Fig. 1: Bretigny, France. Obtained from Google Earth 2003

Four classes, which are Open Area, Wood Land, Built-up Area and Runway, were manually labeled.

Most existing works obtain different image patches through sliding window operation [16]. This method generates smaller images patches by sliding a window through the image with a given stride. In particular, if the stride is smaller than the window size, which is usually the case, the generated image patches will share pixels and ground truth. Several of the mentioned articles divide training and test sets randomly from the generated images. The major drawback is that this overlap will be present between the train and test set. To prevent this issue, we first divide the image vertically into three sub-images as shown in Figure 2. 70% of the image was used as a training set, and 15% was used for both validation and test set. Note that the four classes are present in each sub-image as shown in image 2. The sliding window operation is then applied to each sub-image to generate train, validation, and test set separately. We used a stride of 25 for the sliding window and an input image size of 128×128.

3. COMPLEX-VALUED NETWORK MODEL

To run our experiments, we implemented the CV-FCNN (Figure 3) described on [12] since it is, to our best knowledge,



(a) train (b) val (c) test

Fig. 2: Split of Bretigny dataset; 70% as training set, 15% as validation set and 15% as test set. **A** Built-up Area; **B** Wood Land; **C** Open Area; **D** Runway

the higher claimed performance for PolSAR classification tasks using CVNN techniques. We also implemented an equivalent Real-Valued Fully Convolutional Neural Network (RV-FCNN) to make comparisons against a real-valued network. All implementations were done using the software library [17] published on reference [18]. The code that contains the exact model used for these paper simulations can be found in [19].

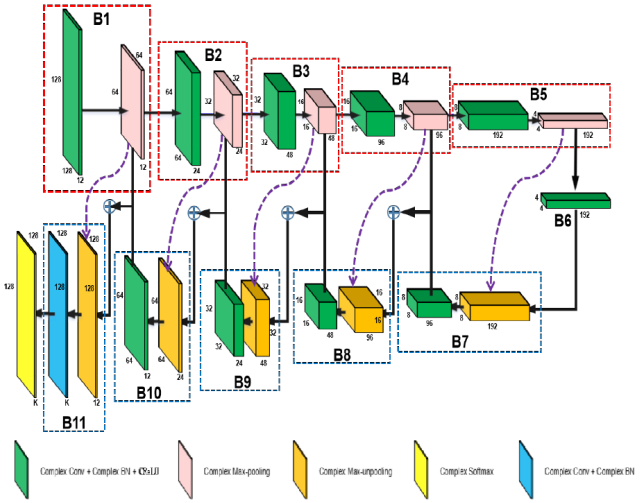


Fig. 3: Complex-Valued Fully Convolutional Neural Network digram extracted from [12]

The models can be divided into three parts, a bottleneck, a down-sampling, and an up-sampling part. These last two sections present an alternation of the main block (shown in green on Figure 3) and the respective down-sampling or up-sampling block. The bottleneck, however, consists of a single main block represented as B6. The main block is a combination of complex-convolution, complex-BN and $\mathbb{C}$ReLU, all explained in reference [20]. Max-pooling (pink) and max-unpooling [21] (orange) are used for the down-sampling and up-sampling parts respectively. The output of the complex network is a complex image with as many channels as classes presented on the dataset (4 in our case). Softmax (yellow) is applied to both the real and imaginary parts separately. The

loss is computed twice, using first the real part and then the imaginary part as the prediction result. An average of the two error values is then calculated to be optimized. It is worth noticing that pixels without labels (black parts on Figure 2) are not taken into account for loss computation and neither for the accuracy metric.

For further details about the implemented models, please refer to [12].

4. EXPERIMENTAL RESULTS

Five Monte Carlo trials of complex and real models were performed for the following results, each involving 150 epochs and a batch size of 30.

In Figure 4, we can see the accuracy and loss curves for both the training and validation set. A solid line represents the mean value, whereas the colored area is the inter-quartile range. In this figure it is possible to appreciate that CV-FCNN generalized better during the ensemble of the training.

Validation loss was used to select the best model checkpoint for each iteration. The final performance was then computed using the test set whose results are displayed on Table 1 with their associated confidence interval. The median error was computed as in [22] who claims that if median intervals do not overlap, there is a 95% confidence that their values differ. The confidence interval of the mean is calculated for a confidence level of 95%.

	CV-FCNN	RV-FCNN
median	92.76 ± 0.36	89.86 ± 0.96
mean	92.77 ± 0.46	89.92 ± 1.23
full range	$93.17 - 92.37$	$91.02 - 88.89$

Table 1: Test Accuracy results (%)

Figure 5 shows the predicted image of a randomly chosen CV-FCNN (5a) and RV-FCNN (5b) models. The Figure allows appreciating the effect of the dataset split method detailed in Section 2 as we see how both models achieve a better representation on the left of the image (training set) and lower performance on the right (validation and test set). On the other hand, it is possible to appreciate that CV-FCNN does a better work predicting the ground truth.

5. CONCLUSIONS

We performed a statistical comparison of a CVNN against an equivalent RVNN on a new PolSAR dataset. We proposed using a new data representation and pre-processing technique that may be more fit for this particular application. Results show a clear out-performance of CVNN over RVNN with both higher accuracy and lower variance. Confidence intervals of the achieved results do not overlap, allowing to assert that CVNN merits over RVNN are statistically justified.

6. ACKNOWLEDGMENTS

We want to acknowledge the Metz campus of CentraleSupélec for providing the DCE cluster to run our simulations.

7. REFERENCES

[1] H. Parikh, S. Patel, and V. Patel, "Classification of SAR and PolSAR images using deep learning: A review," *International Journal of Image and Data Fusion*, vol. 11, no. 1, pp. 1–32, 2020.

[2] B. Konishi, A. Hirose, and R. Natsuaki, "Complex-valued reservoir computing for interferometric SAR applications with low computational cost and high resolution," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7981–7993, 2021.

[3] A. Hirose, *Complex-valued neural networks: Advances and applications*, vol. 18, John Wiley & Sons, 2013.

[4] J. Bassey, L. Qian, and X. Li, "A survey of complex-valued neural networks," *arXiv preprint arXiv:2101.12249*, 2021.

[5] R. Hänsch and O. Hellwich, "Classification of polarimetric SAR data by complex valued neural networks," in *ISPRS workshop high-resolution earth imaging for geospatial information*, 2009, vol. 38, pp. 4–7.

[6] J. A. Barrachina, C. Ren, G. Vieillard, C. Morisseau, and J.-P. Ovarlez, "About the equivalence between complex-valued and real-valued fully connected neural networks - application to PolInSAR images," in *IEEE International Workshop on Machine Learning for Signal Processing (MLSP)*, 2021.

[7] R. Hänsch and O. Hellwich, "Complex-valued convolutional neural networks for object detection in PolSAR data," in *8th European Conference on Synthetic Aperture Radar*. VDE, 2010, pp. 1–4.

[8] Y. Zhou, H. Wang, F. Xu, and Y.-Q. Jin, "Polarimetric SAR image classification using deep convolutional neural networks," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 12, pp. 1935–1939, 2016.

[9] Z. Zhang, H. Wang, F. Xu, and Y.-Q. Jin, "Complex-valued convolutional neural network and its application in polarimetric SAR image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 12, pp. 7177–7188, 2017.

[10] J. Zhao, M. Datcu, Z. Zhang, H. Xiong, and W. Yu, "Contrastive-regulated CNN in the complex domain: A method to learn physical scattering signatures from flexible PolSAR images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 12, pp. 10116–10135, 2019.

[11] Y. Li, Y. Chen, G. Liu, and L. Jiao, "A novel deep fully convolutional network for PolSAR image classification," *Remote Sensing*, vol. 10, no. 12, pp. 1984, 2018.

[12] Y. Cao, Y. Wu, P. Zhang, W. Liang, and M. Li, "Pixel-wise PolSAR image classification via a novel complex-valued deep fully convolutional network," *Remote Sensing*, vol. 11, no. 22, pp. 2653, 2019.

[13] X. Liu, L. Jiao, and F. Liu, "PolSF: PolSAR image dataset on San Francisco," *arXiv preprint arXiv:1912.07259*, 2019.

[14] J. S. Lee and E. Pottier, *Polarimetric radar imaging: from basics to applications*, CRC press, 2017.

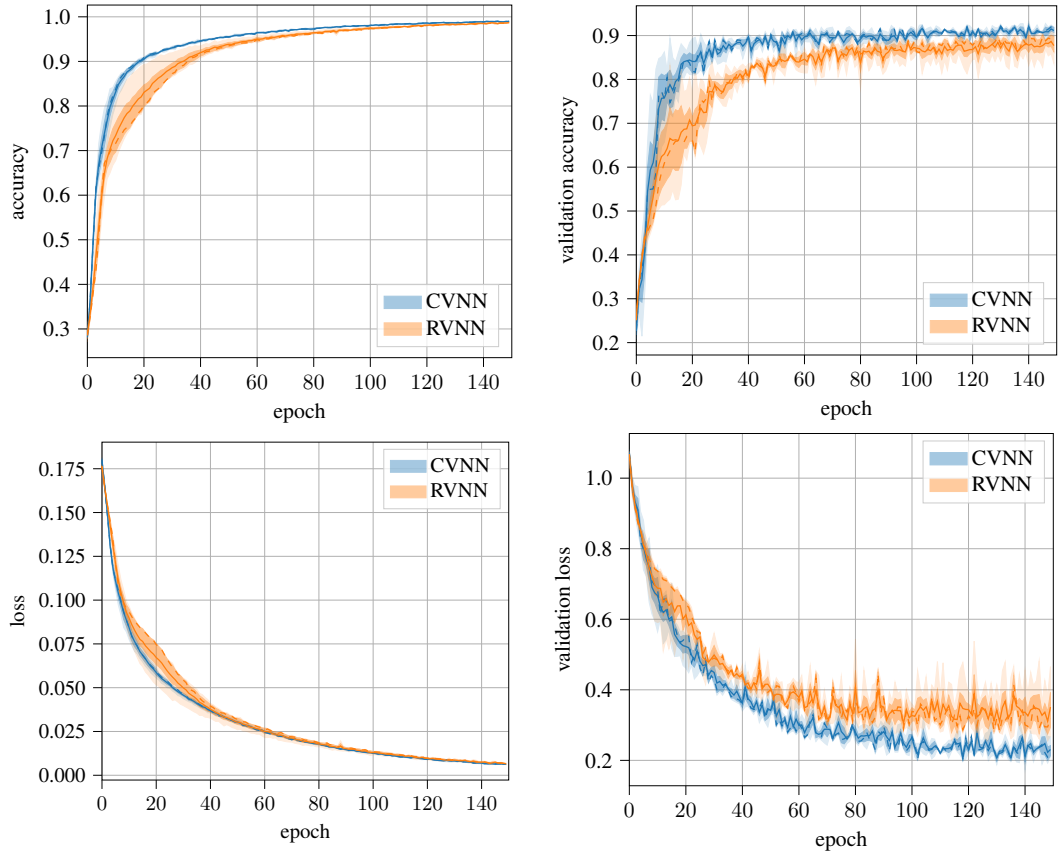


Fig. 4: CV-FCNN vs RV-FCNN accuracy and loss per epoch

(a) CVNN prediction

(b) RVNN prediction

Fig. 5: CVNN vs RVNN predicted image

[15] P. Formont, F. Pascal, G. Vasile, J.-P. Ovarlez, and L. Ferro-Famil, "Statistical classification for heterogeneous polarimetric SAR images," *IEEE Journal of selected topics in Signal Processing*, vol. 5, no. 3, pp. 567–576, 2010.

[16] Y. Li, Y. Chen, G. Liu, and L. Jiao, "A novel deep fully convolutional network for PolSAR image classification," *Remote Sensing*, vol. 10, no. 12, 2018.

[17] J. A. Barrachina, "Complex valued neural networks (cvnn)," Oct. 2021, DOI: 10.5281/zenodo.4452131.

[18] J. A. Barrachina, C. Ren, C. Morisseau, G. Vieillard, and J.-P. Ovarlez, "Complex-valued vs. real-valued neural networks for classification perspectives: An example on non-circular data," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 2990–2994.

[19] J Agustin Barrachina, "NEGU93/polsar cvnn: Antology of CVNN for PolSAR applications," Jan. 2022, 10.5281/zenodo.5821229.

[20] C. Trabelsi, A. Bilaniuk, Y. Zhang, D. Serdyuk, S. Subramanian, J. F. Santos, S. Mehri, N. Rostamzadeh, Y. Bengi, and J. Pal, C., "Deep complex networks," 2018.

[21] I. Zafar, G. Tzanidou, R. Burton, N. Patel, and L. Araujo, *Hands-on convolutional neural networks with TensorFlow: Solve computer vision problems with modeling in TensorFlow and Python*, Packt Publishing Ltd, 2018.

[22] J. M. Chambers, *Graphical methods for data analysis*, CRC Press, 2018.