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 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 using Complex-Valued Neural Network (CVNN) as an alternative to conventional Real-Valued Neural Network (RVNN) for radar applications [3, 4].

Although most works use the Coherency matrix as an input representation, it might not be well suited for complex pixel-wise segmentation tasks 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.

2. EXPERIMENT SETUP

We, therefore, use the Pauli vector as input representation on the ONERA's proprietary PolSAR image of Bretigny, France [5].

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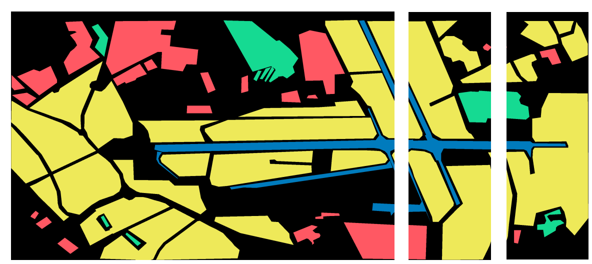
Randomly sampling train, validation and test datasets may produce images very similar from each other. To make matters worse, when using the sliding window operations as done in [6] may even cause images to have coincident pixels. To prevent this issue, we first divide the image vertically into three sub-images as shown in Figure 1. 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 1.



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

Fig. 1: 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

We implemented the CV-FCNN described on [6] since it is, to our best knowledge, 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 [7] published on reference [8]. The code that contains the exact model used for these paper simulations can be found in [9]. 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. Simulations where done on the DCE servers [10].

3. RESULTS

In Figure 2, we can see the accuracy and loss curves for both the training and validation set. A solid line represents

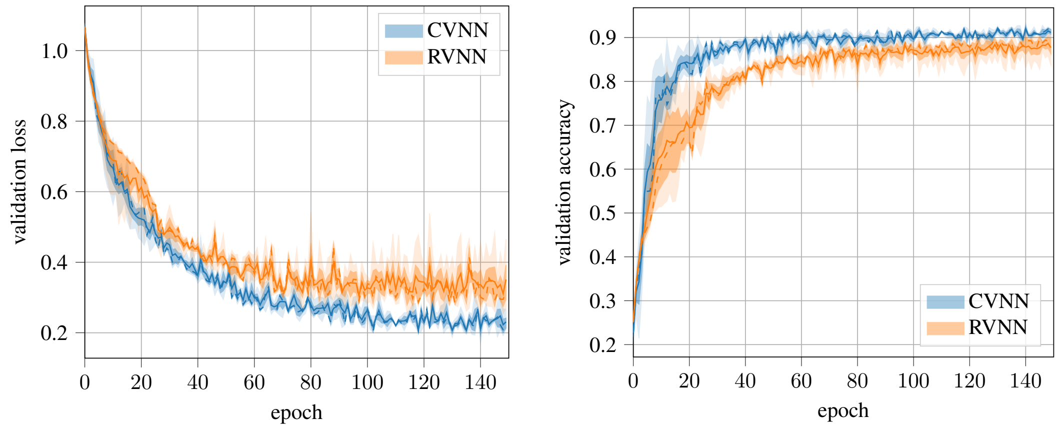


Fig. 2: CV-FCNN vs RV-FCNN validation loss and accuracy per epoch

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. Table 1 show the test accuracy results showing CV-FCNN out-performance where the lowest achieved accuracy of 92.37% outperforms the highest obtained accuracy for the real-valued model which obtained 91.02%. The confidence intervals of both median and mean obtained accuracy allow to assert that CV-FCNN generalize better than RV-FCNN.

	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 (%)

4. 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.

5. REFERENCES

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