Merits of Complex-Valued Neural Networks for PolSAR image segmentation

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Abstract – In this paper, we implement two capacity equivalent neural networks, one complex-valued and the other one real-valued, for Polarimetric Synthetic Aperture Radar (PolSAR) image segmentation. An exhaustive statistical comparison between these two networks are done over the Flevoland PolSAR dataset using the coherency matrix as input. Results show a better generalization for the complex-valued architecture.

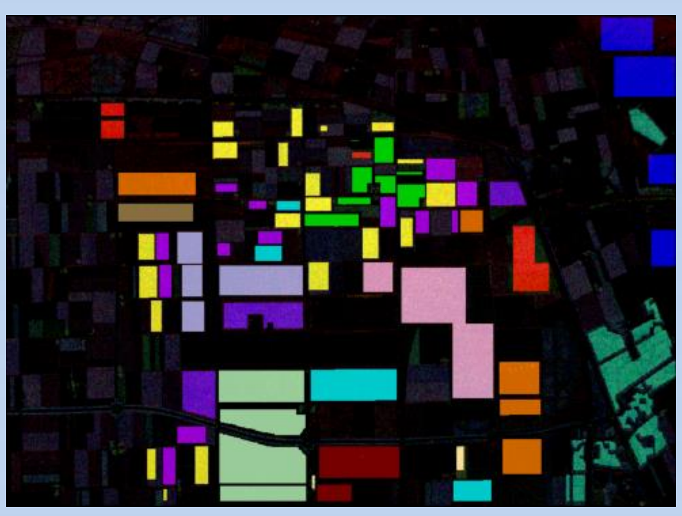
Résumé - Dans cet article, nous mettons en oeuvre deux réseaux de neurones, l'un à valeurs complexes et l'autre à valeurs réelles, de dimensions équivalentes, pour la segmentation d'images Polarimetric Synthetic Aperture Radar (PolSAR). Ces réseaux sont basés sur des architectures convolutives de type {\it U-Net}. Une comparaison statistique exhaustive entre ces réseaux est présentée pour l'image PolSAR de Flevoland, en prenant en entrée la matrice de cohérence. Les résultats montrent une meilleure classification par le réseau de neurones à valeurs complexes.

Dataset

AIRSAR (Airbone Syntetic Aperture Radar)

- NASA / Jet Propulsion Laboratory (JPL)
- Maestro-1 Campaign
- L-Band
- 1989
- Resolution 750x1024

(a) Flevoland PolSAR image



(b) Labels [1]

PolSAR Images are acquired from single look complex data measured in the horizontal (H) and vertical (V) transmit/receive polarimetric channels known as the Sinclair scattering matrix

Sinclair Matrix

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix}$$

Pauli vector

$$k = \frac{1}{\sqrt{2}}\left(S_{HH} + S_{VV}, S_{HH} - S_{VV}, 2S_{HV}\right)^T$$

Coherency Matrix

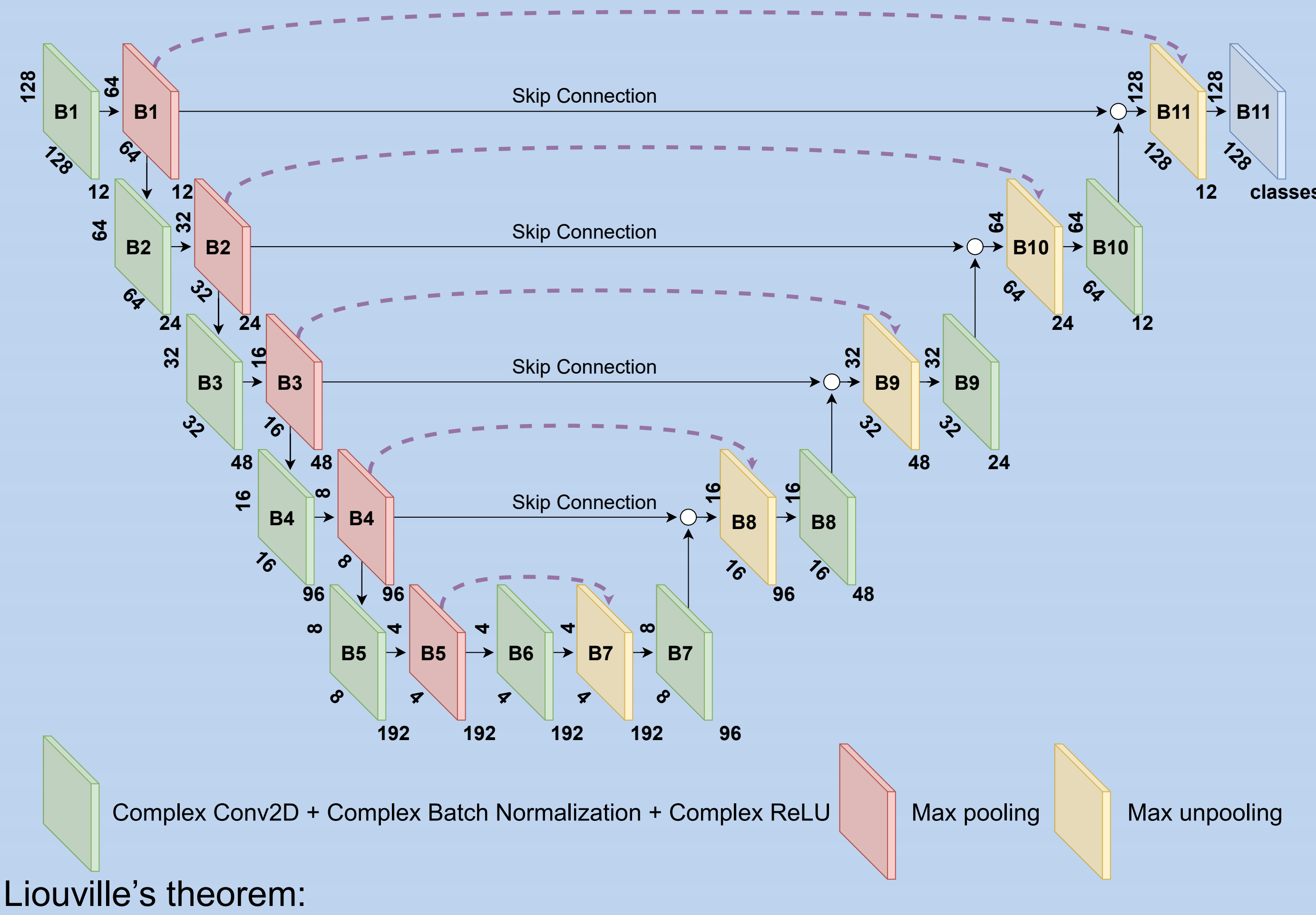
$$\mathrm{T} = \frac{1}{n}\sum_{j}^{n} k_j k_j^H$$

Polarimetric Coherency matrix

- $\mathbb{C}^{3\times 3}$ Hermitian
- Real-valued diagonal
- Total 6 values

Model Architecture

Can complex-valued neural networks exploit phase information to achieve better results than real-valued neural networks? To answer this question, we implement 2 Fully Convolutional Neural Networks, one of them complex-valued inspired by reference [2] architecture. The second model is a real equivalent RV-FCNN model.



Liouville's theorem:

"Given $f(z)$ analytic (differentiable) at all $z \in C$ and bounded, then $f(z)$ is a constant function"

Liouville theorem forces the activation functions to be a constant for the gradient to exist (needed for backpropagation). This is of course unacceptable and therefore, a new definition of the gradient, with the help of *Wirtinger calculus*, is created to solve this problem.

Wirtinger Calculus:

$$\frac{\partial f}{\partial z} = \frac{1}{2}\left(\frac{\partial f}{\partial x} - j\frac{\partial f}{\partial y}\right)$$

Gradient definition:

$$\nabla_z f = 2\frac{\partial f}{\partial \bar{z}} \text{ for } f: C \to R$$

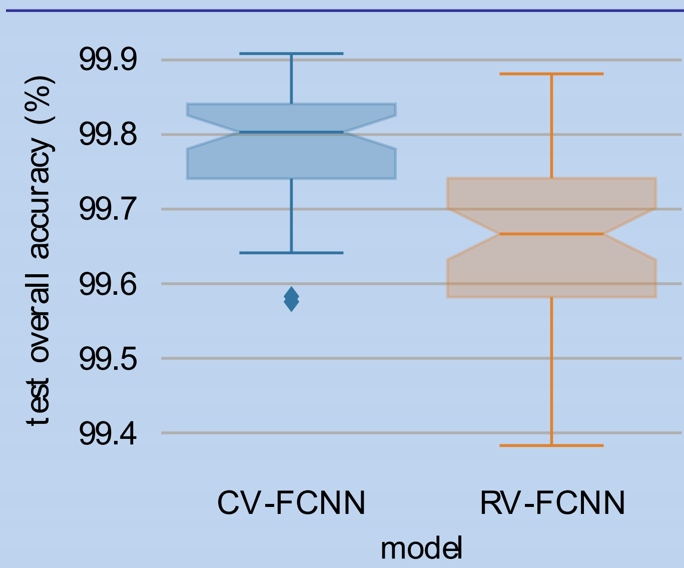
$$f: \mathbb{C} \to \mathbb{R};\ g(z) = r(z) + js(z);\ r, s: \mathbb{C} \to \mathbb{R}, z \in \mathbb{C}$$

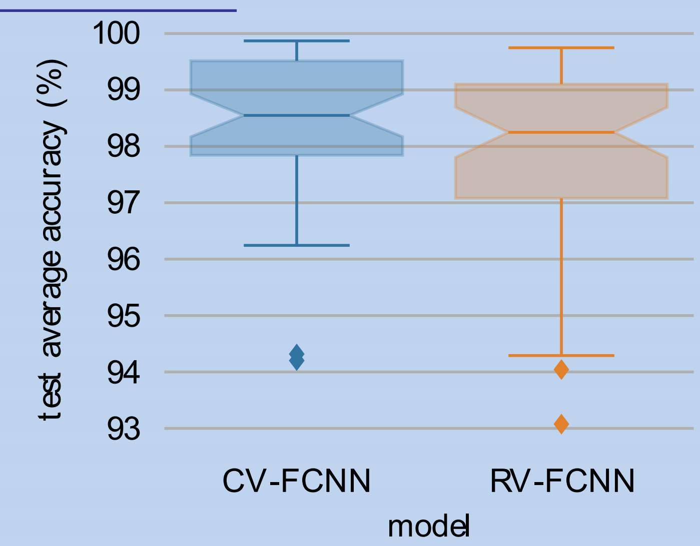
- Loss fuction:
  - Categorical cross-entropy
- Adam
  - Learning rate: 0.001
- Weight initialization:
  - Glorot Uniform [4]
  - Bias initialization: Zeros
- 1000 epochs
  - Batch Size: 100

Results

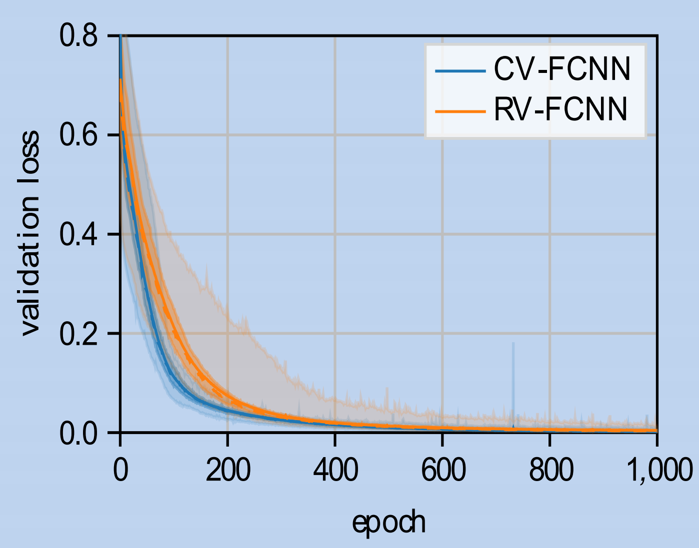
		CV-FCNN	RV-FCNN
Overall Accuracy	Median	**99.80±0.02**	**99.67±0.03**
	Mean	**99.79±0.01**	**99.66±0.02**
	IQR	99.74-99.84	99.58-99.74
	Full range	99.58-99.91	99.38-99.88
Average Accuracy	Median	98.55±0.38	98.25±0.44
	Mean	98.35±0.19	97.87±0.23
	IQR	97.84-99.52	97.08-99.10
	Full range	94.20-99.87	93.07-99.75

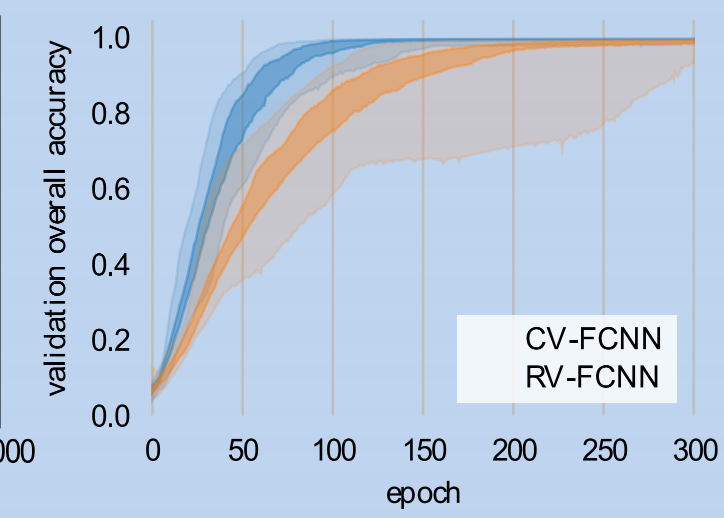
- We illustrate the semantic segmentation performance of these models on the open-source Flevoland PolSAR database.
- FC-FCNN acquired better performance compared to RV-FCNN.
- FC-FCNN lower value of IQR (upper 75%) is higher than the higher value of RV-FCNN IQR (lower 75%).



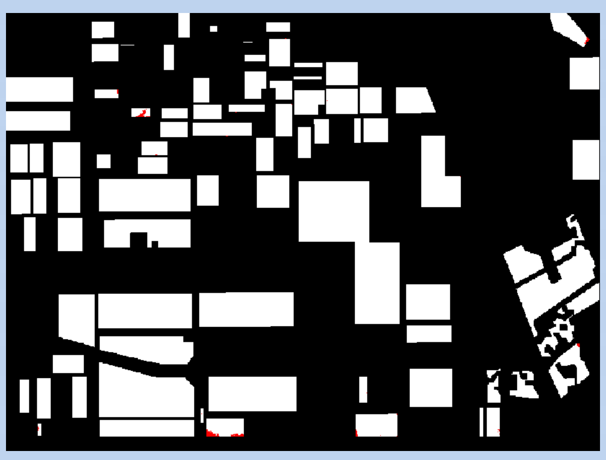


If median intervals do not overlap, there is 95% confidence that their values differ [3]

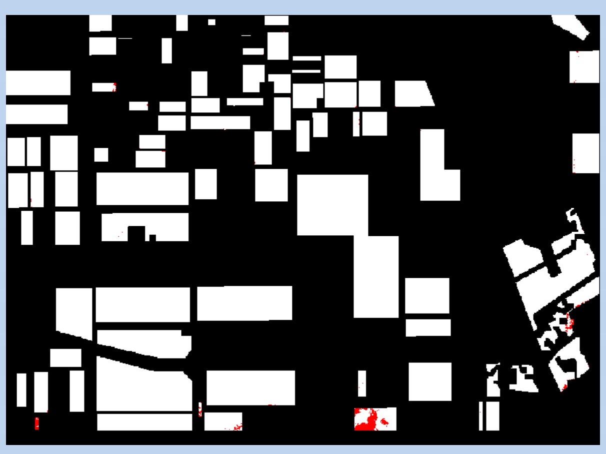




- We can see that CV-FCNN converges faster than RV-FCNN



(a) Median CV prediction



(b) Median RV prediction

References

[1] Z. Zhang, H. Wang, F. Xu and Y. -Q. Jin, "Complex-Valued Convolutional Neural Network and Its Application in Polarimetric SAR Image Classification," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 12, pp. 7177-7188, Dec. 2017, doi: 10.1109/TGRS.2017.2743222.

[2] Y. Cao, Y. Wu, P. Zhang et al. "Pixel-wise PolSAR image classification via a novel complex-valued deep fully convolutional network." *Remote Sensing* 11.22. 2019.

[3] R. McGill, Tukey, J. W., and W. A. Larsen, "Variations of box plots." *The American statistician*, *32*(1), 12-16. 1978.

[4] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, 2010, pp. 249–256.

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