

A SENSITIVITY ANALYSIS OF CNNs TO WIND-GENERATED PATTERS ON X-BAND COSMO-SKYMED SAR SCENES

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INTRODUCTION

Sea surface wind field is a parameter of key importance for several applications that span from weather forecast up to recreation activities.

There is an increasing interest in the exploitation of finer-spatial resolution NRCS measurements acquired by the Synthetic Aperture Radar (SAR). The main challenge relies on that fact that the SAR was not meant to be operationally used for wind field estimation. It can only provide one NRCS measure for each resolution cell and this makes the inversion of the sea surface wind field an under-determined problem [1].

SAR-based wind direction has been addressed using different methods [2]-[3].

Recently, artificial intelligence (AI) methods have been proposed to deal wind direction estimation in with C-band Sentinel-1 imagery [4].

In this study, a sensitivity study is carried out to analyze the performance of neural network (NN) to retrieve wind direction on Cosmo-SkyMed X-band SAR imagery.

METHODOLOGY

The main objective is to estimate the wind direction from the COSMO-SkyMed SAR VV-polarized imagery with artificial intelligence techniques. This is physically possible by exploiting wind-generated patterns in the SAR image, therefore by estimating the orientation of these patterns. The proposed methodology is based on a convolutional neural network (CNN).

The dataset consists of 19 Cosmo-SkyMed data acquired between February and August 2022 in the North Sea area with ancillary measurements acquired on the same area with the ASCAT scatterometer (Advanced SCATterometer) with a maximum time lag of half an hour.

Each SAR image is split into tiles whose size matches the scatterometer pixel, i.e, 10 km. (Figure 1)

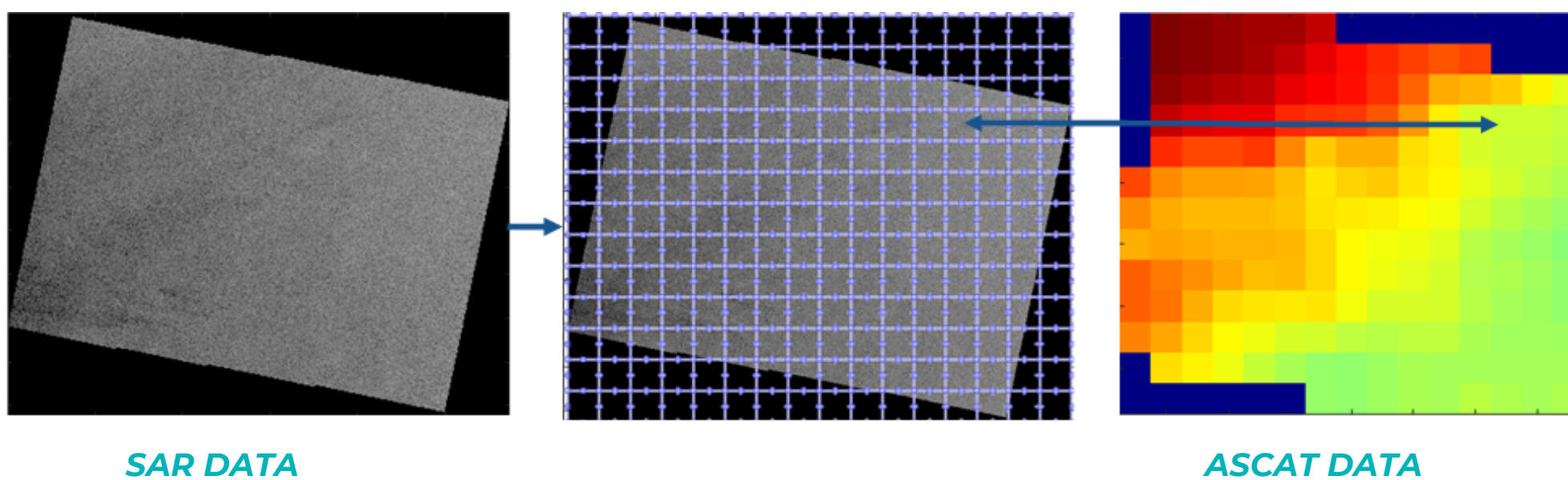


Figure 1 : Dataset partitioning

The multilooked SAR scenes are subjected to a data augmentation technique, which consists of rotating each tile of 90°, 180° and 270°.

The labels were discretized with a granularity of 10 units and the outliers are sorted out.

The final dataset consists of 6608 images, which are split into about 85% for the training, about 10% for the validation and about 5% for the test set.

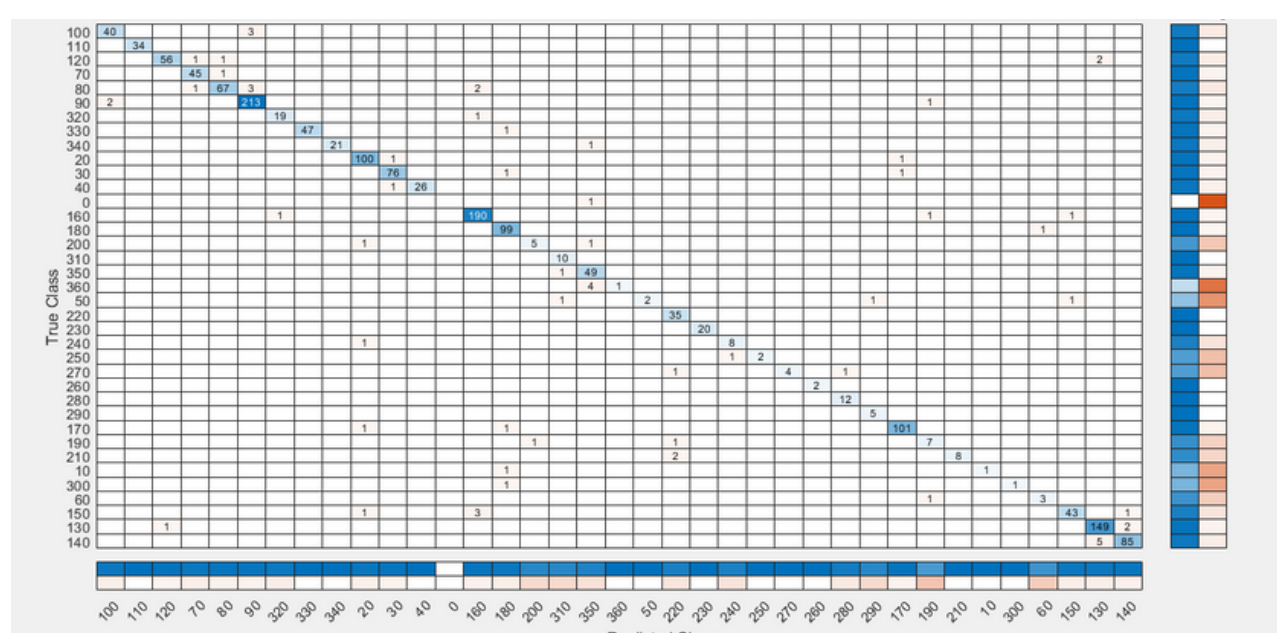


Figure 2 : Confusion matrix

RESULTS

Preliminary experiments are performed to discuss the performance of the retrievals using different CNNs.

The ResNet family is used and the Resnet-18 is found to perform better than Resnet-50 and Resnet-101 that take longer time to train without a significant improvement in the performance with respect to Resnet-18.

The performance of the Resnet-18 is also contrasted with another configuration of CNN, namely Inception v3.

Even in this case, in the classification performance there is no significant improvement.

Anyway, Resnet-18 is faster than Inception v3 in the training phase.

However, ResNet and Inception families result into two completely different paradigms: Resnet allows increasing the number of layers; while Inception allows increasing the number of convolution per layer. A joint use of the two strategies is possible by exploiting the **Inception Resnet v2**. This CNN is used and the results are superior since it reaches a 96% accuracy, whose confusion matrix is shown in Figure 2

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CONCLUSIONS

- The sensitivity of the proposed method with respect to wind direction is good
- The preparation and processing of data are fundamental phases since they significantly influence the learning process.
- The main issues are related to the non-homogeneous distribution of the data used in the learning phase which penalizes some wind directions.
- The best CNN for this task is Inception-Resnet v2

REFERENCES

- [1] Wackerman, C., C. Rufenach, R. Schuchman, J. Johannessen, and K. Davidson, 1996. Wind vector retrieval using ERS-1 synthetic aperture radar imagery. IEEE Trans. Geosci. Rem. Sens., 34, 1343-1352.
- [2] Zecchetto, S., De Biasio, F., Della Valle, A., Quattrocchi, G., Cadau, E., Cucco, A., 2016a. Wind fields from C and X band SAR images at VV polarization in coastal area (Gulf of Oristano, Italy). IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 9 (6).
- [3] Koch, W., 2004. Directional analysis of SAR images aiming at wind direction. IEEE Trans. Geosci. Remote Sens. 42 (4), 702-710.
- [4] A. Zanchetta, S. Zecchetto, "Wind direction retrieval from Sentinel-1 SAR images using ResNet," Remote Sensing of Environment, Volume 253, 2021, 112178, 2021.