

Deep Learning Approach for River Hydro-morphodynamics Monitoring using SAR Data

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Abstract

The knowledge of the hydro-morphological evolution of lowland rivers is essential to develop integrated river management plans. Multispectral and Synthetic Aperture Radar (SAR) Satellite data can be helpful in continuous and efficient monitoring of wet channel evolutions. On the one part, multispectral images are easily interpreted but affected by the presence of cloud cover. Instead, although the SAR images have more complex interpretation, they can provide information in all weather conditions. In this work, a supervised deep learning segmentation method was proposed to analyse the hydro-morphological changes along a reach of the Italian Po River using Sentinel-1 SAR data.

Keywords: deep learning methods, river monitoring, Sentinel-1, Cosmo-SkyMed, wet channel evolutions.

1. INTRODUCTION

The continuous monitoring of fluvial dynamics is essential to know past evolutionary trends and associated drivers, to help water managers and decision-makers in managing hydro-morphology alterations of rivers. Satellite data can provide an effective and cost-effective tool to identify the optimal management practices in the river ecological status and the mitigation of hydraulic risk (Cavallo et al. 2021).

In this work, we used Sentinel-2 (S2) multispectral images with a spatial resolution of 10 m, C-band Sentinel-1 (S1) SAR images in VV and VH polarisations with 10-m spatial resolution. Specifically, the case study is a sediment bar of the Po River (Italy) near the Boschina Island (Ostiglia), characterized by frequent and relevant morphological changes.

2. PROPOSED DEEP LEARNING METHOD

Since Convolutional Neural Networks (CNNs) can approximate complex non-linear functions and has limited computation time thanks to the GPU usage, their usage obtained an increasing interest in many remote sensing applications (Kattenborn et al. 2021; Rezaee et al. 2018). As a drawback, the training phase requires the availability of a large amount of data. In this work, we have used a W-Net architecture that is composed by a cascade of two U-Nets, as described in Gargiulo et al. (2020). In the supervised learning, we needed to produce training examples, specifically input-target pairs. In detail, after the chain of pre-elaborations of S1 images as described in Filipponi (2019), a deep learning architecture was trained starting from the S1 input data, considering as target the water masks extracted from the S2 images. The definition of proper cost functions and learning optimization algorithms is necessary in the learning phase. In this work, we used a cost function, based on Intersection-over-Union (IoU), and for the optimization algorithm the ADAM method, that is an adaptive version of the Stochastic Gradient Descent (SGD). Once the network was trained, it was tested on some of the dates in which very high-resolution images were available.

3. RESULTS

In Fig. 1, the qualitative comparison of the results provided by the deep learning method using Sentinel-1 data with very a high-resolution multispectral image (Fig. 1a) is reported.

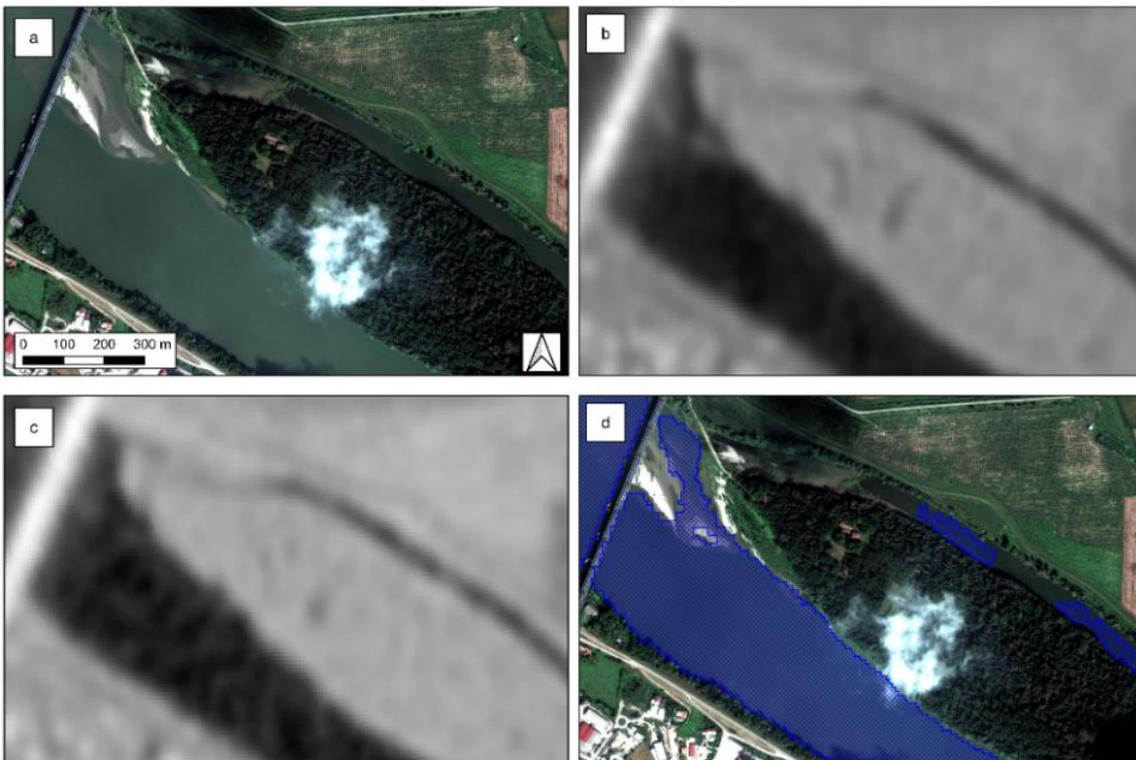


Fig. 1: (a) RGB Geo-Eye-01 (© TPMO 2020) of 16 September 2018 (H= 13.29 m a.s.l.), (b) VV polarization of Sentinel-1 images of 16 September 2018, (c) VH polarization of Sentinel-1 images of 16 September 2018, and (d) the water mask extracted by deep learning algorithm.

As observed in Fig. 1, the co-polarized images (Fig. 1b) are more informative than the cross-polarized (Fig. 1c) in separating between sediments and water pixels. However, both polarizations were useful for extracting the water masks. The water masks extracted from the deep learning algorithm tracks the wet channel with good accuracy (Fig. 1d). Similar considerations can be obtained for the different areas and different dates evaluated.

4. CONCLUSIONS

In this work we have tested a deep learning approach in wet channel monitoring, and we have shown very promising results benefiting by the use of SAR data. The benefits can be more evident in future works, using the X-band Cosmo-SkyMed SAR data images in HH polarisation with 3-m as target of the deep learning method. The achieved results encourage us to exploit a segmentation solution with different features of the riverscape, e.g., sediment bars and vegetation.

References

- Cavallo, C., M. Nones, M.N. Papa, M. Gargiulo, and G. Ruello (2021), Monitoring the morphological evolution of a reach of the Italian Po River using multispectral satellite imagery and stage data, *Geocarto Int.*, 1–23, DOI: 10.1080/10106049.2021.2002431.
- Filipponi, F. (2019), Sentinel-1 GRD preprocessing workflow, *Proceedings* **18**, 1, 11, DOI: 10.3390/ECRS-3-06201.
- Gargiulo, M., D.A.G. Dell’Aglia, A. Iodice, D. Riccio, and G. Ruello (2020), Integration of Sentinel-1 and Sentinel-2 data for land cover mapping using W-Net, *Sensors* **20**, 10, 2969, DOI: 10.3390/s20102969.
- Kattenborn, T., J. Leitloff, F. Schiefer, and S. Hinz (2021), Review on Convolutional Neural Networks (CNN) in vegetation remote sensing, *ISPRS J. Photogramm. Remote Sens.* **173**, 24–49, DOI: 10.1016/j.isprsjprs.2020.12.010.
- Rezaee, M., M. Mahdianpari, Y. Zhang, and B. Salehi (2018), Deep convolutional neural network for complex wetland classification using optical remote sensing imagery, *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **11**, 9, 3030–3039, DOI: 10.1109/JSTARS.2018.2846178.

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