Aerosol layer identification and segmentation from lidar and ceilometer profiles using unsupervised deep learning

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Motivation

- Investigation of the unsupervised deep learning algorithms capability to identify the aerosol layers using synergy of ground-based remote sensing measurements.

Instruments

- Ceilometer type CHM15k having one elastic channel at 1064 nm; photon counting mode of operation.
- Raman multispectral lidar system (RALI) having 7 channels; analog and photon counting modes of operation.

Methods

The features from the attenuated backscatter profiles obtained from lidar and ceilometer measurements are extracted using an unsupervised deep fully convolutional neural network architecture [1] with 300 epochs, batch size = 30, K=15, 1e-4 learning rate; with n-cut loss.

This architecture uses non-annotated data sources and has two tasks learning image segments in an unsupervised way (Figure 1):
1. segmentation of the initial attenuated backscatter profiles;
2. reconstruction of the original input using the information stored in the segmentation. This task has a regularization effect for the first task.

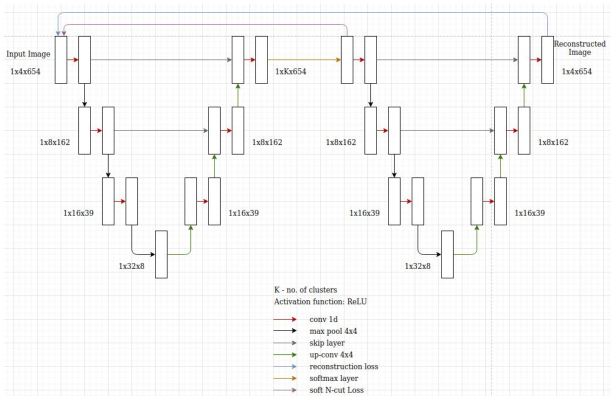

Figure 1: W-net architecture used for unsupervised aerosol layer detection.

Data analysis and results

- The study was performed at the Romanian Atmospheric 3D Observatory – RADO, Magurele, Romania, covering three years (2018–2020) of aerosol remote sensing measurements.
- A dataset with 2816 data points, comprising 2112 lidar (3 channels: 1064 nm, 532 nm, 355 nm) and 704 ceilometer (1 channel) simultaneous atmospheric measurements, was considered. Six of these data points are presented in Figure 2 (top).
- The attenuated backscatter profiles retrieved from lidar and ceilometer measurements were averaged at 5 minutes and with a spatial resolution of 15 m, covering an altitude range from 0.2 km to 10.0 km.

Index	1224	1219	1291	1306	1702	2603
Date	2018.08.27	2018.08.27	2018.09.03	2018.09.03	2018.10.29	2020.05.14
Time	12:19:42	11:54:42	17:41:56	18:52:12	15:18:54	10:21:38

Table 1: Datapoints selected for analysis.

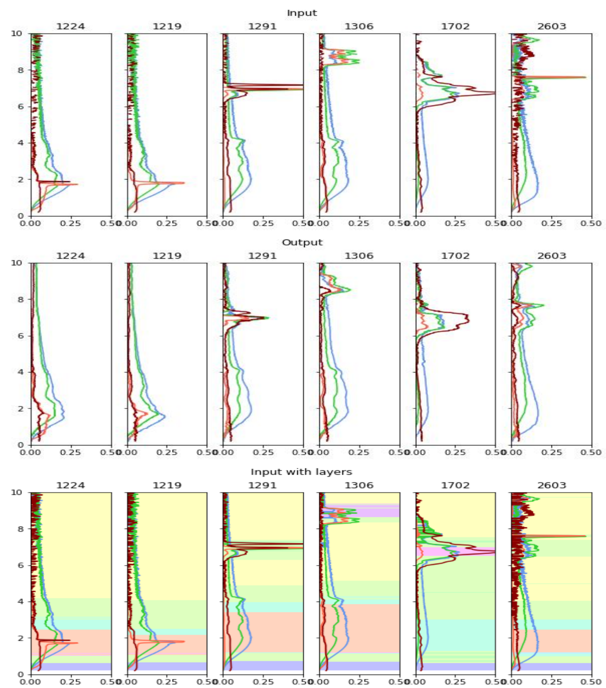

Figure 2: W-net data: Input, output and the layer segmentation.

Discussion

- The W-net architecture used for unsupervised aerosol layer detection (Figure 1) has multiples losses that are used to train both tasks simultaneously.
- The neural network is trained only using attenuated backscatter profiles.
- The model was trained to group together similar values that are close together in height into segmentation that minimize a normalized cut loss [2].
- The reconstruction task forces the network to learn a segmentation that keeps as much of the original information as possible.
- The results presented in Figure 2 show that W-net networks trained in an unsupervised way are able to reconstruct the original signals and segment them into layers.

Challenges

- Optimized model of W-net architecture for identifying layers directly from the data without introducing human biases. The difficult part of this study is making a correct validation of the output of neural networks.
- Cross-validation with the results obtained by the classical methods of layer identification such as the gradient method [3] and wavelet method [4].

Acknowledgments

This work was supported by a grant of the Romanian Ministry of Research and Innovation, CCCDI – UEFISCDI, project number 295PED/2020, within PNCDI III and the National Core Program contract No.18N/2019.

References

1. Xide Xia, and Brian Kulis. W-Net: A Deep Model for Fully Unsupervised Image Segmentation. ArXiv, abs/1711.08506, 2017
2. Meng Tang, Abdelaziz Djelouah, Federico Perazzi, Yuri Boykov, and Christopher Schroers. Normalized Cut Loss for Weakly-supervised CNN Segmentation. ArXiv, 2018
3. Belegante, L., Nicolae, D., Nemuc, A. et al. Retrieval of the boundary layer height from active and passive remote sensors. Comparison with a NWP model. Acta Geophys. 62, 276–289, 2014
4. Cohn, S. and Angevine W. M., 2000: Boundary layer height and entrainment zone thickness measured by lidars and wind-profiling radars. J. Appl. Meteor., 39, 1233–1247