Aerosol classification using a neural network algorithm

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Keywords: aerosol typing, lidar, mass spectrometry.
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This paper presents an algorithm for aerosol classification from optical data derived from multiwavelength Raman lidar measurements. Artificial Neural Networks (ANN) are the basis of the algorithm, due to their capability to deal with noisy signals, to accommodate nonlinear relations and to properly identify the defined classes after a training process (Ali et al., 2013; Bishop, 1995). The method consists in building up a large set of data from simulations for neural networks training purposes and fine adjustments using measurements in order to increase the number of best classified aerosol types.

ANNs with 8 inputs and 14 outputs corresponding to aerosols types, or 7 inputs and 5 outputs are designed for High resolution and Low resolution typing processes, respectively. The ANNs inputs are the standard product of EARLINET's multiwavelength Raman depolarization lidars (Pappalardo et al., 2014): lidar ratios at 355 and 532nm, Angstroem exponent (355/532), linear particle depolarization at 532 nm, color ratios and color indexes (532/1064 and 1064/532).

Generalized feed forward and Jordan/Elman ANNs types have been build up using around 70% of the synthetic database obtained by simulating the optical properties of various aerosol types. Due to the constrain to use statistical significant numbers of cases with known aerosol types to build up and properly train the ANNs, the aerosols intensive optical parameters has been generated using a new developed algorithm which combines the GADS database (Global Aerosol DataSet) with OPAC model (Optical Properties of Aerosol and Clouds) and T-Matrix code (Nicolae et al., 2015).

Several tests have been performed in order to determine the algorithm typing stability and scientific accuracy. A good agreement between synthetic databases used to train the ANNs and available literature and measurements (Groß S. et al., 2013) has been pin pointed. Additional tests on unknown synthetic data assessed the response of the ANNs for cases with data uncertainties, different aerosol concentrations and variable relative humidity. Up to 90% of the aerosols have been properly classified by the High resolution ANNs, and up to 95% by the Low resolution ANNs. Tests on different EARLINET observations have been performed to assess if the algorithm can accommodate data coming from different lidar systems, with or without depolarization capability. According to the High resolution typing algorithm at Bucharest station around 60% of the aerosol layers are continental types, 15% smoke and 15% dust related type. An example of algorithm stability check on both layer height and aerosol types retrieval for both Low and High resolution typing is evidenced in Figure 1.

Also cross validation for certain periods with ground based in situ data are performed in order to identify the aerosols properties and retrieval reliability. The concentration and size distributions of submicronic particles derived from aerosol mass spectrometer measurements specific for biomass burning events are compared with algorithm retrieval for the layers near ground. Smoke, mixed smoke, continental smoke and continental polluted aerosols types are identified, as well as their source and potential to be sensed by in situ instruments.

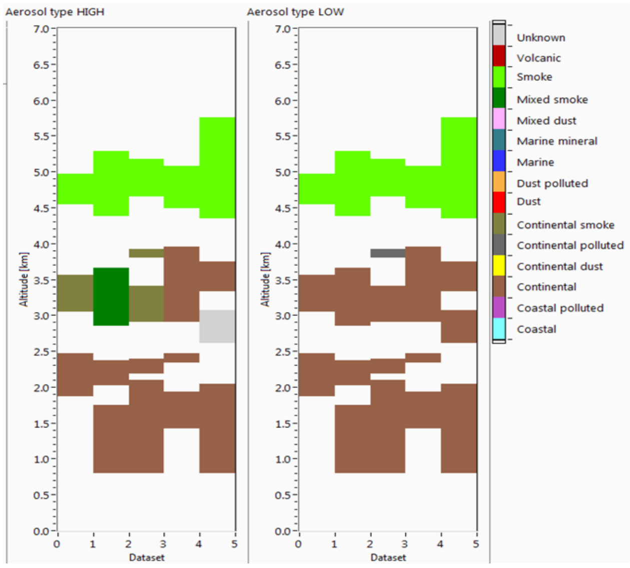

Figure 1. Aerosol classification using typing algorithm based on multiwavelength Raman lidar data

This work has been supported by the ESA contract no. 4000110671/14/I-LG, NATALI, by Core Program, under the support of ANCS, project OPTRONICA IV nr PN 16.40 and by the Programme, Partnerships in S&T priority domain - PNII, MEN – UEFISCDI, project number 309/2014, MOBBE.

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