ATMOS 2015 Advances in Atmospheric Science and Applications, 8-12 June 2015, University of Crete, Heraklion, Greece N.187

Neural-network approach to hyperspectral data analysis for volcanic ash clouds monitoring

Alessandro Piscini*[a], Lucy Ventress[b], Elisa Carboni[b], Roy Gordon Grainger[b] Fabio Del Frate[c]

[a]Istituto Nazionale di Geofisica e Vulcanologia, Via di Vigna Murata 605 Roma, Italy E-Mail: alessandro.piscini@ingv.it ; [b]COMET, Atmospheric, Oceanic and Planetary Physics, University of Oxford, Parks Road, OX1 3PU Oxford, UK; [c]Earth Observation Laboratory, Engineering department Tor Vergata University, Via del Politecnico 1, 00133, Rome, Italy.

Abstract

In this study three artificial neural networks (**ANN**) were implemented in order to emulate a retrieval model and to estimate the volcanic ash Aerosol optical Depth **(AOD),** particle effective radius **(reff)** and **cloud height** from volcanic eruption using hyperspectral remotely sensed data. ANNs were trained using a selection of **Infrared Atmospheric Sounding Interferometer (IASI)** channels in Thermal Infrared (**TIR**) as inputs, and the corresponding ash parameters retreived obtained using the Oxford retrievals as target outputs.

The retrieval is demonstrated for the eruption of the **Eyjafjallajökull** volcano (**Iceland**) occurred in 2010.

The results of validation provided root mean square error (RMSE) values between neural network outputs and targets lower than standard deviation of corresponding target outputs, therefore demonstrating the feasibility to estimate volcanic ash parameters using an ANN approach, and its importance in near real time monitoring activities, owing to its fast application.

A high accuracy has been achieved for reff and cloud height estimation, while a decreasing in accuracy was obtained when appling the NN approach for AOD estimation, in particular for those values not well characterized during NN training phase.

Neural Network Approach

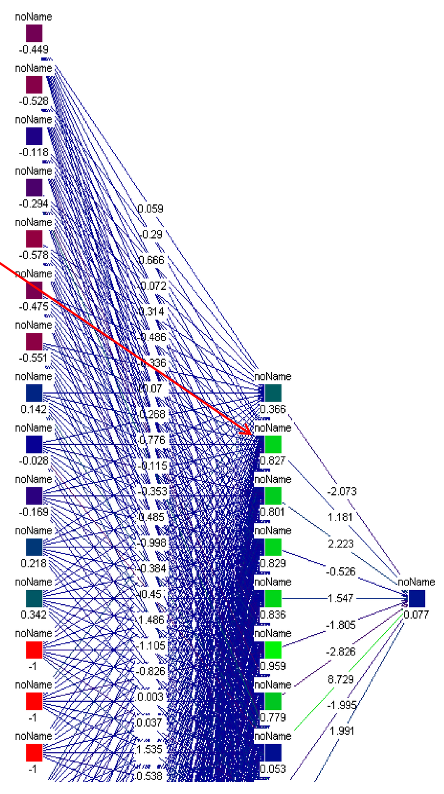
ANN can be seen as mathematical models for multivariate non-linear regression or functional approximation (*Krasnopolsky et al., 1995*).

Relationship between an input space (the space of the data) and an output space is searched using training samples: **Y = Ψ (x , w)** x : vector of independent variables, w : free adjustable parameters

Net effect
$$\xi_j^l = \sum_{i=1}^{N_{l-1}} w_{ji}^l x_i^{l-1}$$

activation
$$x_j^l = \sigma(\xi_j^l) = \sigma\left(\sum_{i=1}^{N_{l-1}} w_{ji}^l x_i^{l-1}\right)$$

sigmoid
$$\sigma(\xi) = \frac{1}{1+e^{-\xi}}$$



Neural Networks

- Inverse modeling;
- Multi Layer Perceptron (**MLP**);
- Back Propagation algorithm (**BP**);
- Early stopping using cross validation (Train, Test and Val set).

Topology

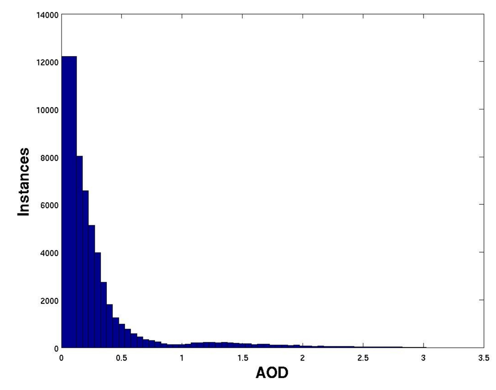
- NN retriever (105 inputs), IASI channels in 8.4 – 14.7 microns spectral range)
- outputs: **AOD** , **Reff**, **cloud height**

Retrieval with IASI:

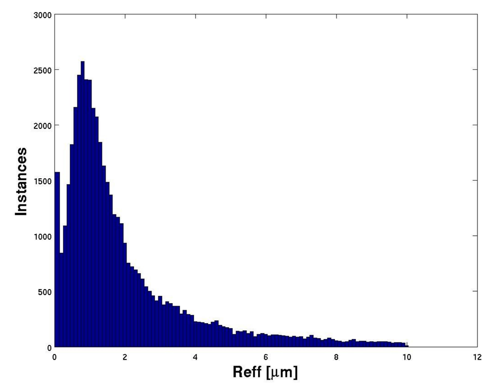
A NN has been built for each parameter that is to be retrieved. The neural networks for the quantitative estimation of the parameters associated with volcanic ash were trained using example results from retrievals carried out using an optimal estimation (OE) technique (*Rodgers, 2000*). The OE retrieval method analyses brightness temperature spectra from IASI and the NN uses the corresponding spectral data as inputs. Assuming a single infinitely thin ash cloud and combining this with the output from the radiative transfer model RTTOV, the OE algorithm produces probable values for the ash AOD, particle effective radius, cloud height and surface temperature, which are the target outputs of the NN.

IASI

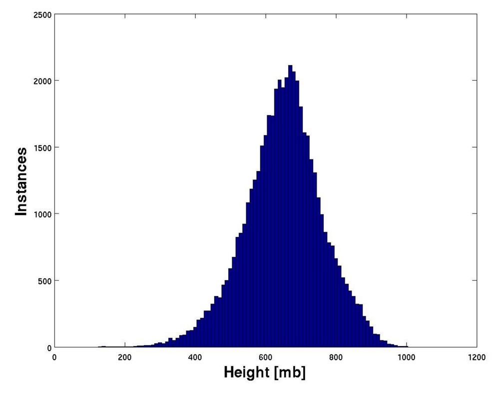
The Infrared Atmospheric Sounding Interferometer (IASI), on board both the **MetOp-A** and **MetOp-B** platforms, is a Fourier transform spectrometer covering the mid-infrared (IR) from 645-2760cm^{-1} (3.62-15.5 mum) with a spectral resolution of 0.5cm^{-1} (apodised) and a pixel diameter at nadir of 12km. These characteristics allow global coverage to be achieved twice daily for each instrument and make IASI a very useful tool for the observation of larger aerosol particles (such as desert dust and volcanic ash) and the tracking of volcanic clouds.



AOD – histogram for dataset used for AOD NN training phase. It put in evidence how values higher than 1 are statistically not well represented.

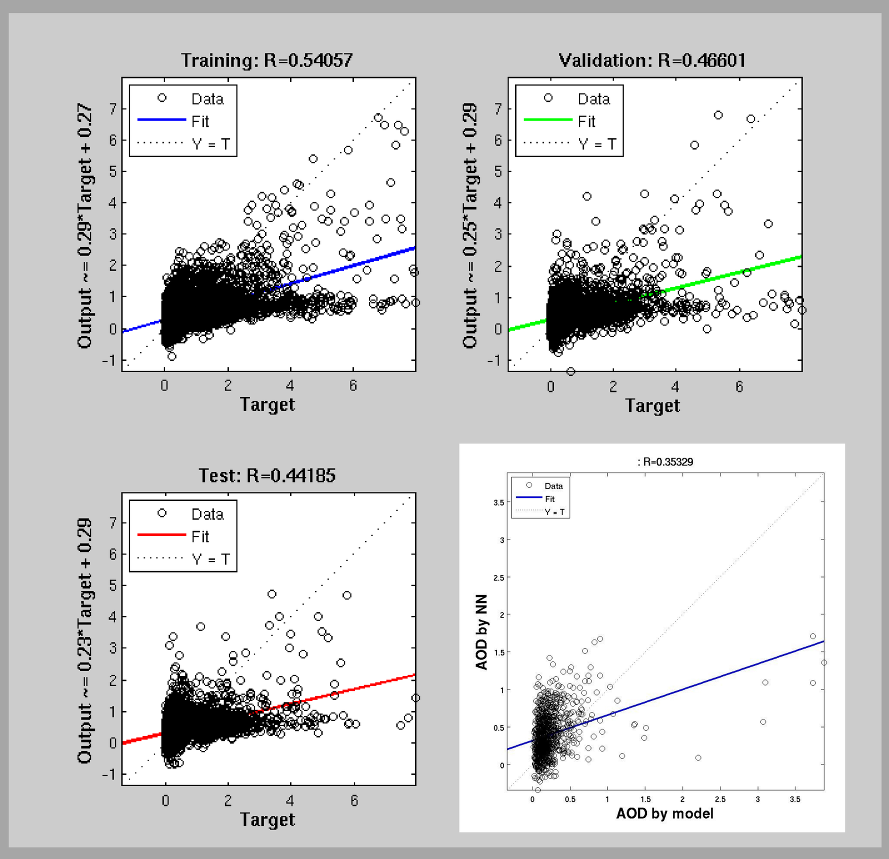


Reff – histogram for dataset used for reff NN training phase. It put in evidence how values higher than 5 microns are statistically not well represented.



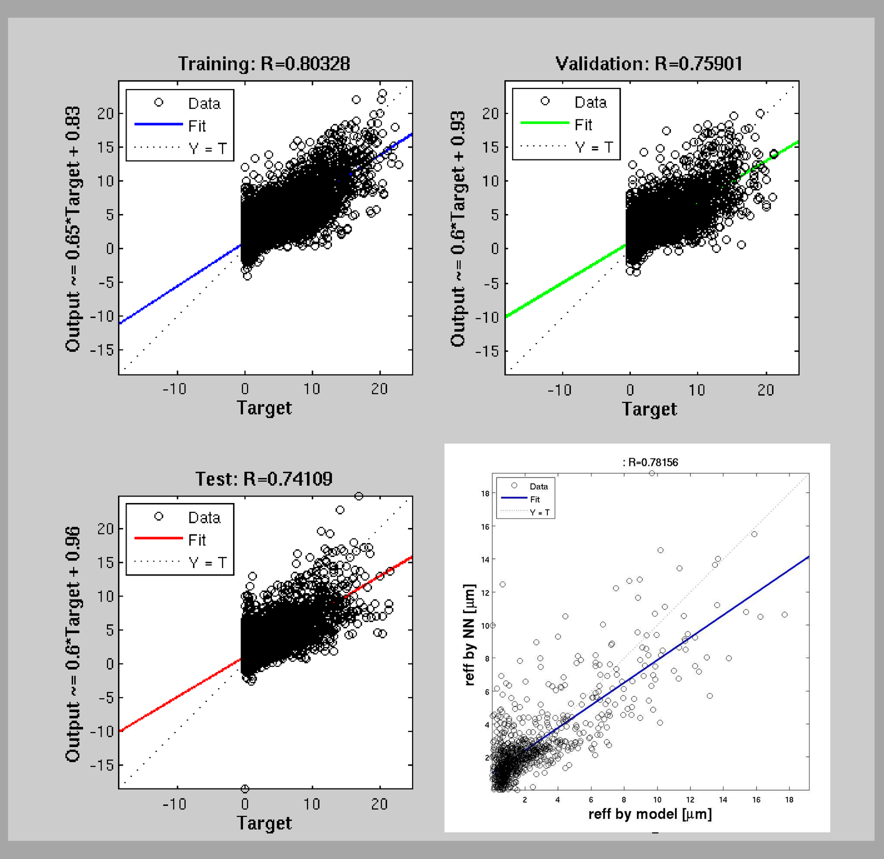
Cloud height – histogram for dataset used for height NN training phase. Tails of distribution describe upper troposphere altitudes and are statistically not well represented.

Results: AOD



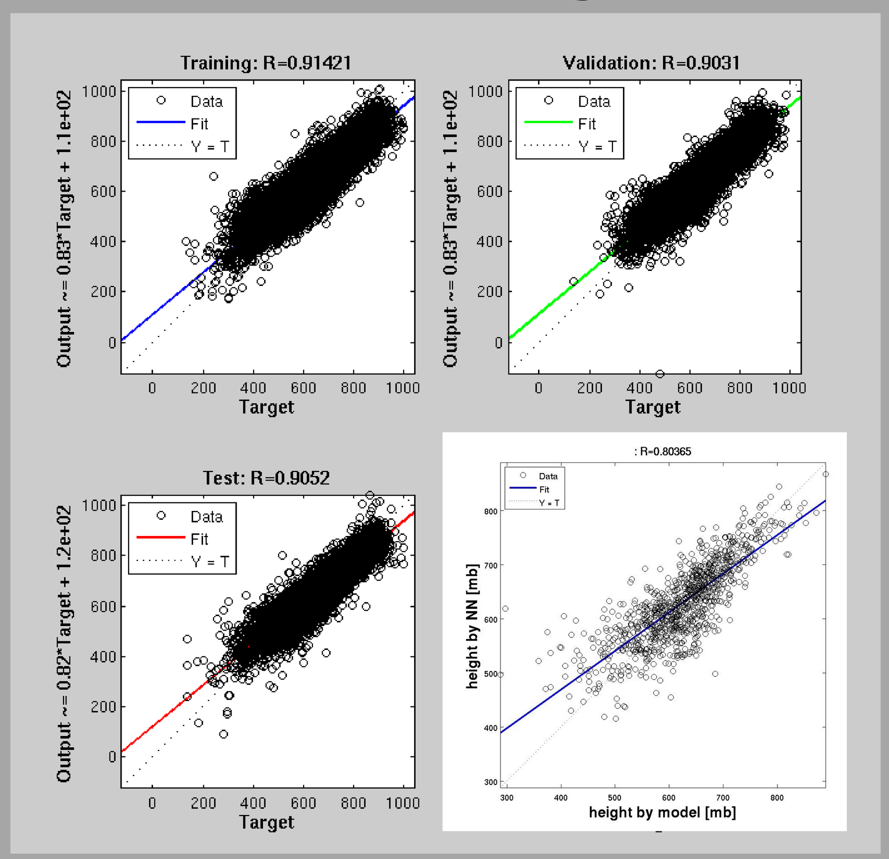
Training, Test and validation scatterplots for AOD, 2010 Eyjafjallajökull eruption. Bottom-right, Validation on 18 May, 2015 , 19:00 UTC eruption.

Reff



Training, Test and validation scatterplots for reff, 2010 Eyjafjallajökull eruption. Bottom-right, Validation on 18 May, 2015 , 19:00 UTC eruption.

cloud height



Training, Test and validation scatterplots for cloud height, 2010 Eyjafjallajökull eruption . Bottom-right, Validation on 18 May, 2015 , 19:00 UTC eruption.

The networks proved to be very effective in solving the inversion problem related to the estimation of the parameters of the volcanic cloud once the training phase is complete.

The validation carried out on the scene from the 18 May 2010, 19:00 UTC, Eyjafjallajökull eruption showed that the Root Mean Square Error (RMSE) of the outputs remained lower than the Standard Deviation (STD) of the targets, which demonstrates a good performance in network generalization capability. In particular, the NNs show high accuracy in retrieving ash effective radius and cloud height but reveal a loss of accuracy for AOD, in particular when the values are statistically not well characterized during training phase.

Conclusions

NNs provide a fast inversion technique, which is useful for the application to volcanic monitoring. From this point of view the technique satisfies the need to respond quickly as a result of disastrous natural hazards, such as volcanic eruptions. In order to use NN approach in near real time monitoring care has to be taken during training phase. This is because the neural network needs to be fed and trained continuously during its operating phase in order to maintain phenomena knowledge updated and retrieval's performance accurate at operating stage.

Future activities will include testing the effectiveness of the technique under cloudy conditions.

References

V. M. Krasnopolsky, L. C. Breaker, and W. H. Gemmill. A neural network as a nonlinear transfer function model for retrieving surface wind speeds from the Special Sensor Microwave Imager. J. Geophys. Res., 100(C6):11033{11045, 1995. doi:10.1029/95JC00857.

Rodgers, C. D.: Inverse Methods for Atmospheric Sounding: Theory and Practice, World Scientific, River Edge, NJ, USA, 2000.