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Atmospheric Measurement Techniques
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Discussions

Interactive comment on "A neural network approach for the simultaneous retrieval of volcanic ash parameters and SO₂ using MODIS data" *by* A. Piscini et al.

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The proposed manuscript presents an approach for the retrieval of volcanic ash parameters from remote sensing data by using a classical NN approach. The paper is confuse in some points and difficult to read. However, my main criticism concerns the novelty of the proposed approach. In particular, the use of a NN approach for the retrieval of biophysical parameters from remote sensing data is not new and already exploited in [1] by the same authors for the retrieval of volcanic ash from MODIS images.

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Answer: the authors thanks anonymous referee for significant comments, but they would like also to underline that manuscript novelty is that NN approach has been applied, for the first time, to MODIS multispectral data for retrieving also volcanic ash particle size and AOD, whilst in [1] NN was applied only for ash mass retrieving. Furthermore, NN approach has been used for retrieving the SO2 concentrations. In the case all MODIS channel were exploited a pruning algorithm has been implemented for extracting the more significant MODIS channels from input data-sets. Finally, great effort has been made in order to extend the retrieval algorithm also for those cases when a volcanic cloud lies on meteorological cloud, a situation not considered in conventional volcanic ash and SO2 retrieving methods.

Aside from the novelty issue, there are many other problems that need to be addressed:

Page 3351 lines 25-27: The authors claim that the NN by default requires a very low computational time. However, the computation time is related to the topology of the NN, to the number of cycles and the number of samples used in the training phase. These parameters can drastically change the computational load of the training phase of the NN. On this regard, to my knowledge there is not a consolidated technique to correctly select the optimal topology of the NN. This means that several attempts, varying the number of nodes in the hidden layers should be made in order to select the best results.

For these reasons I don't believe that NNs can be characterized by a low computational time. I suggest the authors to revise this sentence and provide a direct comparison of computational times obtained with different approaches.

Answer: in the text cited we asserted: "Furthermore its strength is represented by a very low computation time required during application phase, so that the computational burden required for the data processing is drastically reduced". So once training phase has finished, we meant the NN approach reveals a fast method at application stage. As regard NN training phase we agree with reviewer that many approaches exist in order to find the best topology. We adopted a heuristic one, and several attempts have

AMTD

7, C1735–C1740, 2014

been made, varying the number of nodes in the hidden layers in order to select the best results.

Page 3357 line 25: The Authors should be more clear. It is not clear if the concept of NN as "universal approximator" has been introduced in Cybenko 1989 or in Krasnopolsky, 1995.

Answer: Cybenko introduced the concept of ANN as “universal approximator” in 1989, and Krasnopolsky extend the concept proving being able to model physical nonlinear phenomena and to solve complex inversion problems.

Page 3358 line 14: I think the authors are making confusion between DN and physical measures.

Answer: We agree to reviewer and we explained not very well the concept. Following text: “For remote sensing applications, usually, the input layer collects values in the form of Digital Numbers (DNs), e.g. radiances or brightness temperatures, from spectral bands through a number of nodes equals to the number of bands.” has been changed with: “For remote sensing applications, usually, the input layer collects values data such as radiances or brightness temperatures from spectral bands through a number of nodes equals to the number of bands.”

Page 3358 line 19: As the authors proposed the back-propagation method they should also explain which activation functions have been chosen. This is a crucial point when performing retrieval using NN. In fact, while a nonlinear activation functions in the output nodes may be useful for the training phase, they also tend to compress the highest and lowest values, having a negative impact in the retrieval phase. I suggest the authors to further discuss this problem and propose a valid solution.

Answer: we agree with reviewer and following text has been added in order to describe activation function used in the study.

“The BPNN adopted featured rescaled sigmoidal activation function in each node,

AMTD

7, C1735–C1740, 2014

where (-1,+1) output range tends to be more convenient for neural networks."

Page 3358 lines 23-25: In biophysical parameter retrieval tasks the selection of training samples is extremely important and should be better explained.

Answer: cross validation approach has been better explained.

Following text: "In this phase two data sets called training and test have been respectively used to change the weights and to stop the training algorithm before the generalization capability started decreasing. To assess the network performance of the trained net, a third independent data set (validation set) is usually used."

has been changed with:

Training with cross validation was carried out by splitting the training data into three sets: a training set, a cross validation set and a test set. These consisted respectively of 55%, 25% and 20% of the total number of training samples. The first set was used for network training. The cross validation set, consisting of 25%, was analyzed at a predefined number of epochs, to assess performance on datasets other than the training one. Finally, the test set (20%) was used as an independent data source to assess network performance after the training phase.

Page 3559 lines 7-12: There exist better feature selection approaches that work better than pruning. The pruning approach, usually tends to fit the NN to the training data.

This means that the pruning reduces the generalization ability of the NN. I ask the authors to take into account this problem.

Answer: Training data used in this study was representative of an atmospheric scenario involving volcanic clouds in order to let ANN to model the volcanic parameters from input sensor radiances. We are quite confident that pruning analysis carried out was able to select significant input in MODIS sensor able to characterize the target involved also when independent data-set were used. Regarding the choice done, we focused on it taking into account simultaneously the model and the data (this is usu-

AMTD

7, C1735–C1740, 2014

ally the case for ANN variable selection). We decide to adopt Optimal Brain Surgeon (OBS) method, which is similar to Optimal Cell Damage (OCD) proposed by Cibas et al. (1996). Both methods use the hessian of the cost function for computing the cost function dependence upon input unit weights, but the latter seem to be more effective because uses the whole hessian matrix for computing weight saliencies. As regard other feature selection approaches we agree with reviewer of existence of other methods, but in order to select the best one, we'd have carry out a comparison of different approaches, a study which is out of scope of this work.

Page 3361 lines 22-26: I believe that using pixels from the image for the training of the NN for the retrieval is not a good choice. Visual inspection and interpretation is in my opinion not a good validation approach because there isn't any certainty on the effective correspondence between the measured spectra and the expected parameters.

Answer: Just for clarification, only independent data-sets, not used in training phase have been used for validation and pixel have been flagged "sea" and "cloudy" (those described in tables 4 and 5). The distinction between "sea" and "cloudy" pixel has been carried out by means an algorithm that exploits reflectance measured at MODIS channel 3, sensitive to land/cloud spectral properties.

Since the cross validation has been previously explained, in order to avoid confusion, following text: "For each date of the training dataset, three distinct subsets have been created, such as Training, Test and a Validation sets, and they are summarized in Tables 2 and 3, while the two validation dates are shown in Tables 4 and 5. The independent validation pixels have been further split in sea and clouds, depending on where the ash plume were lying, in order to evaluate also the capability of the NNs to deal with these two distinct scenarios;"

has been changed with:

"Validation dates are shown in Tables 4 and 5. The independent validation pixels have been further split in sea and meteorological clouds, depending on where the ash cloud

AMTD
7, C1735–C1740, 2014

were located, exploiting reflectance measured in channel 3 of MODIS, in order to evaluate also the capability of the NNs to deal with these two distinct scenarios."

[1] Picchiani, M., Chini, M., Corradini, S., Merucci, L., Sellitto, P., Del Frate, F., and Stramondo, S.: Volcanic ash detection and retrievals using MODIS data by means of neural networks, Atmos. Meas. Tech., 4, 2619–2631, doi:10.5194/amt-4-2619-2011, 2011.

Cybenko, G.: Approximation by superpositions of a sigmoidal function, Math. Control,Signals,S yst.2 ,303-314, 1989.

Krasnopolsky, V. M., Breaker, L. C., and Gemmill, W H.: A neural network as a nonlinear transfer function model for retrieving surface wind speeds from the special sensor microwave imager, J. Geophys. Res., 100, 11033–11045, 1995.

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Interactive comment on Atmos. Meas. Tech. Discuss., 7, 3349, 2014.