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Neural-Network approach to hyperspectral data analysis for volcanic monitoring of sulphur dioxide

[(a)]Alessandro Piscini, [(b)]Elisa Carboni, [(b)]Roy Gordon Grainger, [(c)]Fabio Del Frate

(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, Civil Engineering and Computer Science Engineering Department Tor Vergata University, Via del Politecnico 1, 00133, Rome, Italy

1. Abstract

This study is about an **Artificial Neural Network** (**ANN**) algorithm that recognizes volcanic **sulphur dioxide (SO_2)** in the atmosphere using hyperspectral remotely sensed data from the **Infrared Atmospheric Sounding Interferometer Instrument** (**IASI**) instrument aboard the METOP-A satellite. The remote sensing of volcanic SO_2 is important because it is used as a proxy for volcanic ash which is dangerous to aviation and is generally more difficult to discriminate.

In this paper an ANN algorithm is demonstrated on date of the eruption of the **Eyjafjallajökull** volcano (Iceland) during the months of April and May 2010, and on the **Grímsvötn** eruption occurring during May 2011.

The algorithm consists of a **two output neural network classifier** trained with a time series consisting of some hyperspectral eruption images collected during Eyjafjallajökul 2010 and eruption and Grímsvötn 2011 eruption. The **inputs** were all channels (441) in the **IASI ν_3 band** and the target outputs (truth) were the corresponding **Oxford retrievals of SO_2** amount.

The classifier was validated on four independent IASI orbits, two that included observations of the Eyjafjallajökull eruption and two that included observations of the Grímsvötn volcanic eruption that occurred in May 2011.

The validation results for the Eyjafjallajökull independent data-sets had an **overall accuracy** of 100%. The validation of the neural network classifier on images from the Grímsvötn eruption shown lower overall accuracies due to the presence of **omission errors**. Statistical analysis revealed that those **false negatives** lie near the detection threshold for discriminating pixels affected by SO_2. This demonstrated that the accuracy in classification is strictly related to the sensitivity of the model.

Nevertheless results obtained underlined that no commission errors were present at the validation stage (pixels erroneously labelled as affected by SO_2) and the method has shown the same accuracy when applied to IASI images with different illumination conditions (morning and afternoon orbits) and in cloudy sky conditions.

2 Data: measurements and retrievals

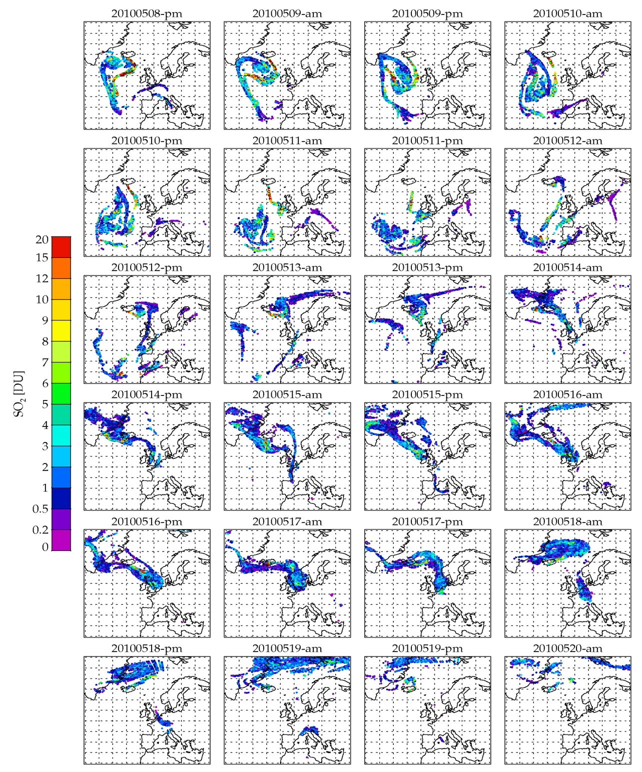
2.1 METOP IASI sensor

The IASI sensor is aboard Meteorological Operational Program (**METOP**) satellite, a European weather satellite which has been operating since 2007. METOP is the first of three satellites scheduled to operate for fourteen years. It crosses the Equator on the descending node at a local time of 9.30. IASI is a Fourier transform spectrometer which covers the spectral range 645-2760 cm^{-1} (3.62 to 15.5 μm) with spectral sampling of 0.25 cm^{-1} and spectral resolution of 0.5 apodized cm^{-1}. It has a nominal radiometric accuracy of 0.25–0.58 K. The field-of-view (FOV) consists of four circular footprints of 12 km diameter (at nadir) inside a square of 50 × 50 km, step-scanned across tracks (30 steps). It has a 2000 km wide swath and nominally it can achieve global coverage in 12 h.
IASI is the only infrared spectrometer on board METOP with global coverage every 12 hours (METOP A), and now that METOP B is available there should be no coverage gaps.

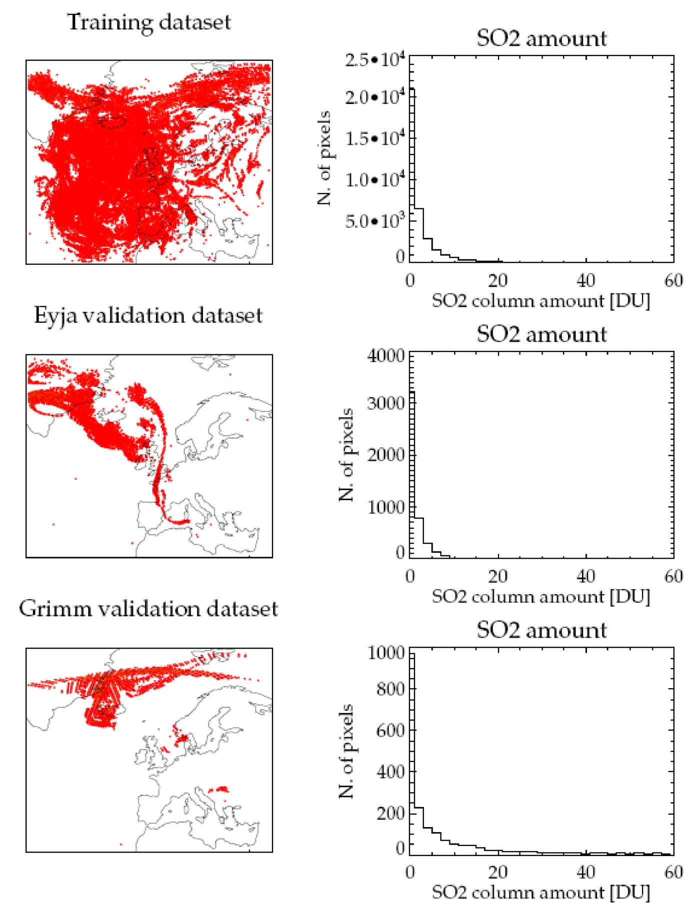
2.2 SO_2 retrieval description

Values used here as **training examples** were obtained with the optimal estimation scheme to retrieve **SO_2 column amount** and altitude from nadir satellite thermal infrared measurements using the two SO_2 absorption bands centred at about 8.7 and 7.3 μm, the ν_1 and ν_3 bands respectively and more details of the retrieval are in Carboni et al. (2012). This retrieval technique uses a new approach to compute and use an error covariance matrix, Se, based on an SO_2-free climatology of differences between the IASI measurements and forward modelled spectra. Any differences not related to SO_2 between IASI spectra and those simulated by a forward model are included in the covariance matrix, allowing a comprehensive error budget to be computed for every pixel.

The IASI retrieval follows the method of Carboni et al. (2012) where SO_2 concentration is modelled by a Gaussian profile. The optimal estimation technique of Rodgers (2000) is then used to estimate SO_2 column amount and the height of the SO_2 profile, and the surface skin temperature using IASI measurements from 1000 to 1200 cm^{-1} and from 1300 to 1410 cm^{-1} (the v1 and v3 SO_2 bands).



IASI SO_2 column amount, divided into morning and afternoon orbits, for the period from 8 to 20 May 2010.



Spatial distribution maps of IASI SO_2 (left), divided into training set (top), Eyjafjallajökull validation dataset (middle), Grímsvötn validation dataset (bottom) and SO_2 total column content statistical distribution for each dataset represented by histograms (right).

3. Neural Network methodology

In this work Backpropagation Neural Networks (**BPNN**) have been used (Hassoun 1995). A BPNN is an Multilayer Perceptron (**MLP**) consisting of an input layer with nodes representing input variables to the problem (**x**), an output layer with nodes representing the dependent variables (i.e., **Y** what is being modeled), and one or more hidden layers containing nodes to capture the non linearity in the data. Using supervised learning, with the Error-Correction Learning (**ECL**) rule for network weights adjustments, these networks can learn the mapping from one data space to another using examples. **Cross validation** can be used to detect when overfitting starts, during supervised training of the neural network; training can then stopped before convergence to avoid overfitting, a process called **early stopping** (Prechelt 1998).

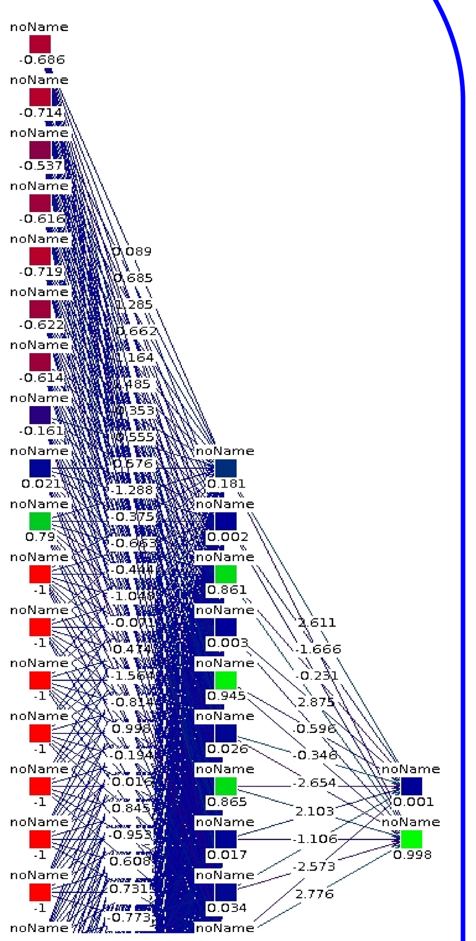
A neural network for SO_2 detection was implemented using a training set of 59 **IASI** images, spanning the April-May 2010 Eyjafjallajökull and May 2011 Grímsvötn eruptions (Iceland). The training sets used IASI retrievals from Carboni et al. (2012) as representative of SO_2 class and pixels not flagged as SO_2 by detection method of Walker et al. (2012) for representing "non SO_2" class.

$Y = \Psi(x_i, w_i)$

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

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

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



The total number of training samples was 74614, of which 43437 were classified as SO_2 affected of which 84% belong to the Eyjafjallajökull eruption.
The network topology consists of 441 inputs, namely the brightness temperatures in the 1300–1410 cm^{-1} channels, the so-called ν_3 band, comprising the range of wavelengths containing information used for SO_2 amount estimation.
Ten neurons were used in a single hidden layer, in order to cope with non linearly discrete problems (Hecht-Nielsen, 1990). Finally, outputs consisted of the two possible classification results, namely "SO_2 " and "non SO_2".

References:
Carboni, E., Grainger, R., Walker, J., Dudhia, A., and Siddans, R., 2012. A new scheme for sulphur dioxide retrieval from IASI measurements: application to the Eyjafjallajökull eruption of April and May 2010, Atmos. Chem. .Phys., 12, 11417-11434, doi:10.5194/acp-12-11417-2012.
Hassoun, M.H., 1995. Fundamentals of Artificial Neural Networks, MIT Press, Cambridge, MA.
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Prechelt, L., 1998. Automatic Early Stopping Using Cross Validation: Quantifying the Criteria, Neural Networks, 11(4), 761-767.
Rodgers, C. D., 2000. Inverse Methods for Atmospheric Sounding: Theory and Practice, World Scientific, River Edge, NJ, USA.
Walker, J. C., Carboni, E., Dudhia, A., and Grainger, R. G., 2012. Improved detection of sulphur dioxide in volcanic plumes using satellite-based hyperspectral infra-red measurements: application to the Eyjafjallajökull 2010 eruption, J. Geophys. Res., 117, D00U16, doi:10.1029/2011JD016810.

4. Results

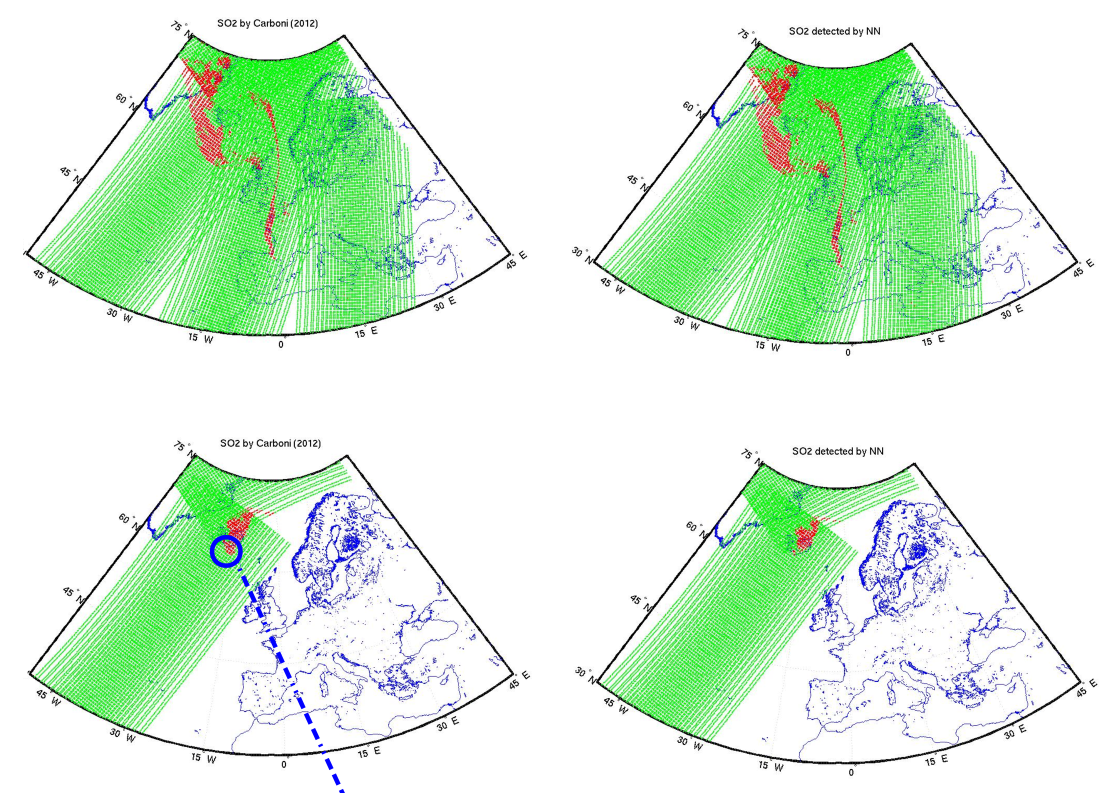
Performance was assessed in terms of **overall accuracy** and **Producer accuracy**. The former represents the percentage of correct classifications, with respect to the total number of pixels analysed, considering all classes (i.e. "SO_2 " and "non SO_2"). The Producer accuracy instead represents the percentage of correct classifications with respect to the total obtained for that output class and it is an **omission error indicator**.
The resulting **confusion matrices** associated with application to independent datasets spanning two **Eyjafjallajökull** volcanic eruptions revealed an accuracy of 100% on both tested images.
The results of applying the ANN classifier to the **Grímsvötn** eruption reveals an accuracy lower in detecting SO_2 plume, but these cases included:
a) The data-sets belonging to the Grímsvötn eruption represented a minor percentage of IASI time-series used as training samples;
b) the presence of **false negatives**, i.e. pixels affected by SO_2 not detected. In this case an analysis carried out on false negatives for both validation dates revealed that those pixel belonged to the portion of the plume at **tropospheric** altitudes where the sensitivity of the method is lower.
Nevertheless, the neural network classifier has been shown to work well on both daytime and night-time images and in cloudy sky conditions, and it successfully **overcame the detection of false positives** present in the validation dataset images, whose presence in multispectral or hyperspectral images can often undermine the performance of traditional classification algorithms.

NN classifier confusion matrix

Overall Acc.: 100%		SO_2		Prod. Acc. (%)
		Yes	No	
NN	Yes	1823	0	100
	No	0	37180	100

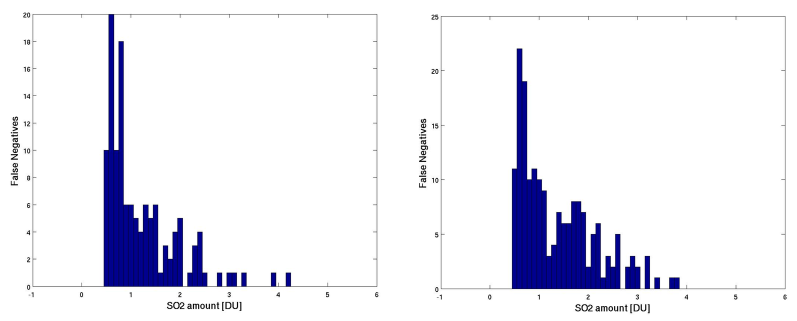
Overall Acc.: 99.1%		SO_2		Prod. Acc. (%)
		Yes	No	
NN	Yes	298	0	70.3
	No	126	13865	100

Classification of IASI images by Carboni et al. (2012) **NN mapping**

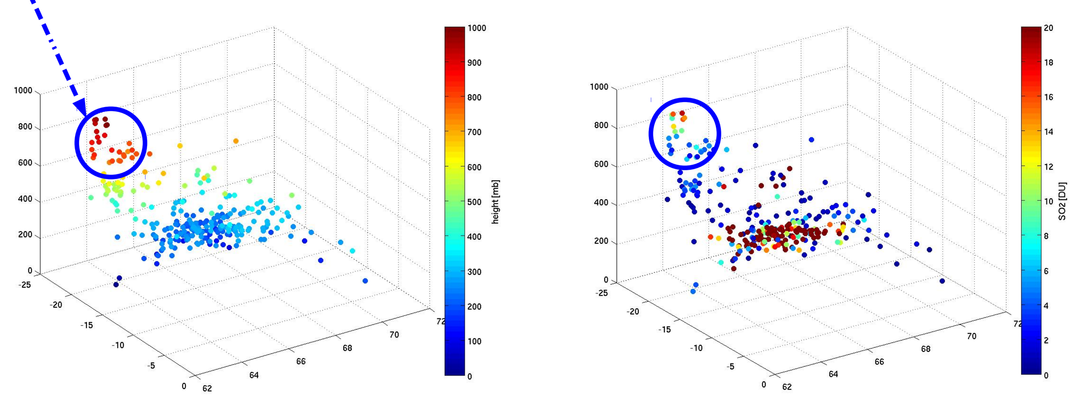


Comparison between SO_2 retrieved by Carboni et al. (2012) (left) and SO_2 map from ANN classifier (right) for **Eyjafjallajökull May 15, 2010 morning orbit**. Pixels affected by SO_2 are coloured red, pixels not affected by SO_2 are coloured green.

Grímsvötn May 22, 2011, 12:00 UTC. Pixels affected by SO_2 are coloured red, pixels not affected by SO_2 are coloured green.



SO_2 amount distribution, considering only false negatives, for **Grímsvötn May 22, 2011, 12:00 UTC** (left) and **May 22, 2011, 20:00** UTC (right). Both histograms reveal that most values have an amount around the SO_2 detection threshold.



Grímsvötn May 22, 2011, 12:00 UTC. Plume SO_2 concentration and height maps (left and right).