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Brief paper

A Soft Computing Approach to the Elaboration of Satellite Data

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Abstract. In this work a soft computing approach, based on a neural network methodology, is presented; it is aimed to retrieve atmospheric parameters of meteorological interest such as temperature, water vapor and ozone profiles from high resolution infrared sensor spectra. Specific neural network has been developed on basis of the specifications of the Infrared Atmospheric Sounding Interferometer (IASI). The performance of the neural network based inversion methodology has been evaluated by considering an inversion case in which test cases are retrieved. Given the nature of available data, a preliminary elaboration of spectra by means of principal component analysis has made, and an online adaptive pruning of the network during training is performed. The adaptive pruning is based on a bi-local technique and allows optimizing the network size and architecture.

Keywords. Feedforward neural networks, meteorology, pruning techniques, satellite applications.

1 Introduction

During the last years, the use of high spectral resolution infrared sensors aimed at sensing the lower atmosphere to weather forecasts is largely enhancing. Nevertheless, applications of soft computing (SC) in this field are still limited [1,2]. On the other hand a SC approach, because of its intrinsic capability of handling uncertain and noisy data, represents a powerful tool for the inversion issue in such a class of problems. This paper describes a neural compound system designed to invert geophysical parameters. In particular, the inverse problem related to atmospheric parameters of meteorological interest such as temperature, water vapor and ozone profiles from high resolution infrared sensor spectra measured by the Infrared Atmospheric Sounding Interferometer (IASI) is considered. IASI is a part of the core payload of European Polar System (EPS) of European organization for the exploitation of Meteorological Satellites (EUMETSAT).

The spectrometer will be launched to support operational meteorology and climate monitoring. The package is being specified to possess the high spectral resolution required to achieve the sounding quality improvement, which the community of meteorologist considers mandatory in order to improve Numerical Weather Prediction. In addition, the instrument is expected to give information on greenhouse trace gases and on surface and cloud properties: sea surface temperature, land surface temperature and emissivity, cloud transmittance and reflectance. The instrument is a spectrometer interferometer with a spectral coverage of 645 to 2760 cm^{-1} and a spectral resolution of 0.25 cm^{-1}. This range includes absorption bands by CO_2, H_2O and all relevant trace gases in addition to window region to derive surface and cloud properties. It is designed to reach the accuracy of 1 K for temperature profiles and 10% for humidity, at least in lower troposphere with a vertical resolution between 1 and 2 km in the troposphere, as required by the World Meteorological Organization (WMO). IASI has 8461 potential channels to be exploited for inversion of geophysical parameters, and new problems concerning data pre-processing and processing arise [3].

The classical approach to retrieve geophysical parameters from infrared radiance relies on physical inversion schemes which are inevitably extremely slow, then the computation time required for solving the inverse problem becomes prohibitive, especially when inversions are aimed at endowing of weather forecast numerical models, which have to be real-time. Artificial neural networks (ANN) can be considered a suitable alternative technique because of their computational efficiency and their possible ability to provide the first guess to initialize the physical schemes.

One of the main problem with high spectral resolution sensors is handling the high redundancy of the information content of the data. In this work, the extraction of characteristic features and projection of data on lower-dimensional spaces have been performed by the principal component analysis (PCA) [4] approach in which the information is extracted by finding the directions in the *n*-dimensional input data space along which the data elements possess the largest variations. Moreover, in order to correctly dimension the appropriate network, a pruning adaptive algorithm is applied during the training of the network; this allows us to avoid both underfitting and overfitting drawbacks, locating a right work-point. The work is a further development of previous one of the same authors [5-7] and the capability of the neural network based inversion methodology has been evaluated by computer simulations.

2 System Architecture Development

The data sets of IASI synthetic spectral radiances have been generated on the basis of the line-by-line forward model σ-IASI [8] and refers to clear-sky conditions and nadir view angle. σ-IASI is a radiative transfer model designed to match the spectral range of the IASI interferometer and it has been designed for fast computation of spectral radiance. This model is based on a look-up table of monochromatic optical depths and an interpolation procedure. Basically, it is an accelerated version of LBLRTM (Line-by-Line Radiative Transfer Model, version 4.3 [9]) fully parameterized for IASI.

The methodology behind σ-IASI is mainly based on two key points: 1)- double thresholding of the optical depths, and 2)- their parameterization with respect to temperature and gas concentration. σ-IASI yields radiance and its derivatives both for clear and cloudy atmosphere, although for this study it has been used to yield clear-sky spectral radiance only. The inhomogeneous nature of the atmosphere along a radiation path is most readily treated with the so-called plane-parallel assumption which implies that variations in the intensity and atmospheric parameters (temperature and gaseous profiles) are permitted only in the vertical direction (e.g. pressure). In this approximation, the vertical nonhomogeneity of the atmosphere is handled by sub-dividing it into a set of layers and by choosing the number and the height of the layer boundaries in such a way that 1) each layer may be thought of as an isothermal layer, 2) the gas within each layer may be considered homogeneous.

The noise is generated at unapodized level at the IASI sampling rate using a random number of generator producing normally distributed random numbers, (we are deal with the problem that the IASI noise is only partially known) then each random series is apodized (the apodization process is required to limit the effects of the finite path length of the mirror of an interferometer on a narrow spectral line and, from a mathematical point of view, its effect is equivalent to a convolution of the ideal interferogram with a smooth truncation function) and added to each synthetic IASI spectrum to yield the given IASI observation.

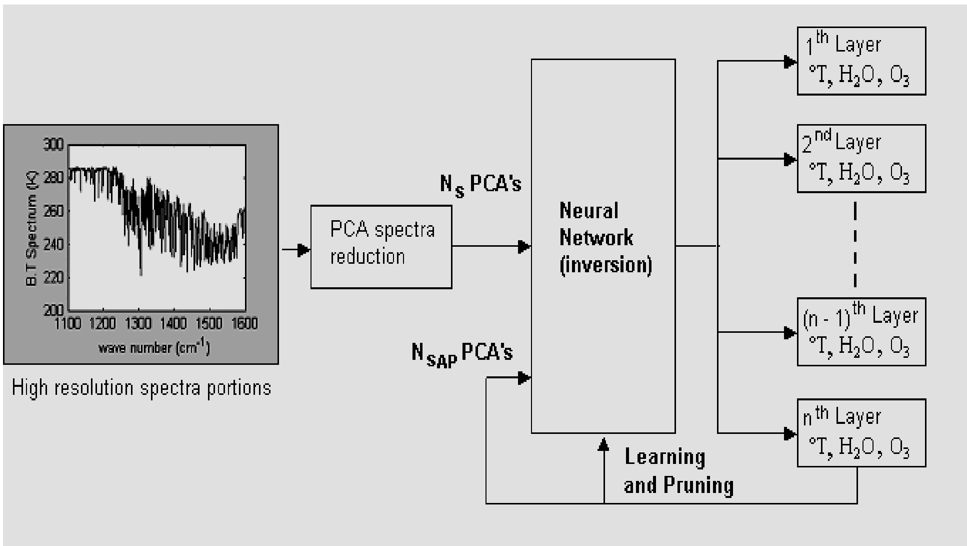

Fig. 1: Neural System architecture

In Fig. 1, a representation of the overall inversion system proposed is given. It is described in the following paragraphs.

3 The Neural Network

The implementation of the neural system is a multilayer back propagation feedforward network.

After some preliminary approaches [6], the topology of the system comes now from a simultaneous strategy: temperature, water vapor and ozone are simultaneously retrieved at each layer (Fig. 1). The present architecture of the net is generic and can be, therefore, specialized to different instruments and atmospheric layering by changing the appropriate input parameters.

The following choices have been done:

- the first forty σ-IASI atmospheric layers have been used to represent the atmosphere from the ground level to the average altitude of the ER-2 airplane, assumed to be 20 km; consequently forty neural nets have been implemented and trained which corresponds to the forty atmospheric layers from 0 to 20 km. Each neural net yields the triplet (T, H2O, O3), corresponding to a given atmospheric layer;
- the surface temperature is included in the first network, which then has four outputs;
- the large number of channels (8461) makes full spectra handling prohibitive. Thus, convenient subsets of channels have been selected according to the characteristics of absorption by gaseous constituents of the earth's atmosphere. This pre-elaboration leads to a spectral radiance vector which is obtained by considering the following four spectral ranges: 1. 670-800 cm^{-1}; 2. 1010-1080 cm^{-1}; 3. 1350-1450 cm^{-1}; 4. 2160 2260 cm^{-1}, for a total of 1604 spectral data points.

The total number of 1604 selected spectral ordinates is still too huge to directly present all channels to the network. Moreover, the information content of these channels is highly redundant so the input may be efficiently reduced by resorting to a principal component analysis pre-elaboration. On this way the data space (spectral radiance) is initially represented through 50 Principal Components obtained by a truncated Hotelling transform of the original radiance vector.

The Hotelling or PCA transform is obtained by Singular Value Decomposition of the training data-set covariance operator [10]. This initial choice guarantees a projection fidelity index of 99.5%. The 99.5% fidelity index means that the retained 50 components contribute 99.5% of the total variation (variance) in the data set.

The initial range of parameters of the network (where they are randomly distributed) has been determined by some empirical test to obtain a good convergence rate. The network consists of the input layer, two hidden layers, the first one of 40 neurons and the second one of 10 neurons, and 3 neurons of output (4 in the first network which includes surface temperature). Training algorithm is backpropagation with nonlinear sigmoidal neurons [10].

4 Local Sensitivity Evaluation and Pruning Techniques

The developed architecture is effective, but still a drawback is present. This is due to a couple of principal issues:

- The high number of input channels requires the use of PCA as explained before, and it is not so simple to choose how many principal components to use. Fidelity index can be used, but it is not a fully reliable indicator.
- A compromise between complexity (better approximation on training data but overfitting risk) and velocity (underfitting and bad local optima risks) must be found. Number of neuron and consequently of connection is initially chosen high, in order to guarantee a good approximation of training data. On the other hand the set of data available for training is not so large and a clear problem of overfitting is resulting after the training of the network.

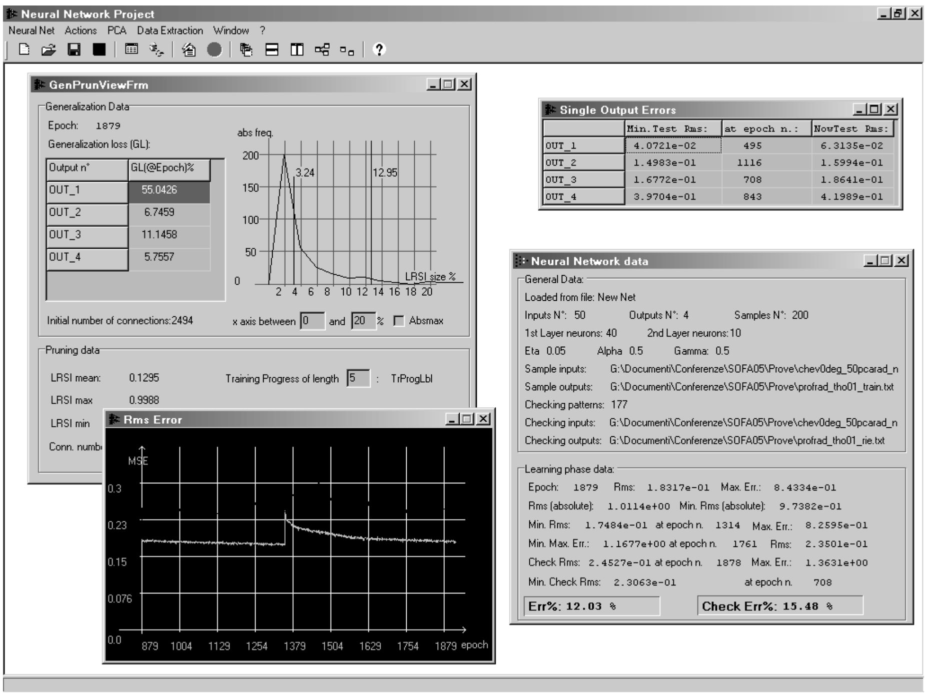

Fig. 2: Neural system simulation program **ν²IASI**

For this reasons a further development is proposed, by introducing a pruning procedure during training phase. This result into a twofold aim: a correct evaluation of effectively needed input space dimension and a drastic reduction of the net dimension, improving generalization quality. Pruning is performed by using a local procedure based on the calculation of a sensitivity index LSI [11]:

$$LSI_{ji} = \frac{\left|SV_{ji}\right|}{\sum_{m=1}^{n}\left|SV_{jm}\right|} \; ;$$

$$SV_{ji} = \sum_{n=0}^{N-1}\left[\frac{\delta}{\delta w_{ji}}\left(\sum e_j^2\right)\cdot \Delta w_{ji}\right]\times \frac{w_{ji}(\,final)}{\left(w_{ji}(\,final) - w_{ji}(initial)\right)},$$

where:

j, i are the node indexes (each neuron being a node);

w_{ji} is the weight of the connection between the node *i* and the node *j*;

e_j is the j^{th} error, i.e. the distance between the target and the actual j^{th} output.

n is the number of connection in the given layer;

N is the number of training iterations.

Sensitivity is backpropagated together with error computation and extended to all the layers of the network. Connections are pruned which are less significant than a cut-off value $\beta = \mathbf{f}(\lambda, \mu_{LSI})$, where μ_{LSI} is the mean of the distribution of *LSI* over a single layer and λ is a parameter dynamically varied to take under control the generalization quality of the training process.

Pruning does occur when a check on the loss of generalization quality suggests us to do it and it can be repeated more times during training. In Fig. 2, the program $\mathbf{v^2}$**IASI** developed by authors for the simulation of the system is shown.

5 Results

The initial choice for the layer dimensions includes $40\times(50+1) + 10\times(40+1) + 3\times(10+1) = 2483$ weights (the first network 2494), that is large in comparison with the number of sample cases. So the network initially presents a good approximation capability of the training set, but a rapid deterioration in validation error. On the other hand a lower dimension of input space and of network size in the initial choice could inopportunely lead to a sub-optimal network.

Table 1

Neural network behavior before and after pruning

	Before pruning (epoch 350)	After pruning (epoch 1085)
Surface T° (error in K)	0.53	0.43
1^{st} air layer T° (error in K)	1.62	1.59
H_2O (rms % error)	13.96	13.37
O_3 (rms % error)	34.76	32.80
Input dimension	50 (N_s)	28 (N_{sAP})
Total weight number	2494	562

In Table I, some results are given (regarding a validation set of data), limited to lowest layer and to one only pruning step. It must be taken into account that first pruning step is in any case the most important one, also if successive refinements can be eventually done using in adaptive way the cut-off value β. Input size has decreased from the initial 50 principal components to 28; the other 22 inputs have been dumped by the pruning process itself, so they can be discarded with no information loss. The error adjustments are not huge, but the overall procedure allows not only an improvement of generalization, but also a correct dimensioning of input and network size. On the other hand a very promising result stands out from the table and the errors are very close to the required standard of the satellite apparatus which is ±1 K in 1 km in the troposphere, and ±10-20% accuracy in lower tropospheric layers of 1-2 km depth, for temperature and water vapor, respectively. Ozone result is found being less than 10% in stratosphere, as required (the value relating to Ozone in Table 1 is over 30%, but it is taken in the low troposphere region).

6 Conclusions

The soft computing approach adopted in this work allows us to invert high resolution infrared spectra with respect to important atmospheric parameters, exploiting a combination of PCA, neural networks with backpropagation training algorithm and pruning techniques. In particular pruning techniques allow an interesting fine-tuning of the results and an optimization of the network size in order to stay inside required specifications, which are almost satisfied by the given approach. In any case, this architecture could provide a valid “first guess” to sequentially initialize suitable physical inverse schemes which may fully restore the accuracy within the IASI mission objective.

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