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RETRIEVAL OF ATMOSPHERIC TEMPERATURE FROM HIRS MEASUREMENTS USING NEURAL NETWORK APROACH: OPERATIONALIZATION AND VALIDATION

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ABSTRACT: This paper aims to present the use of artificial neural network (ANN) to retrieve vertical temperature profiles from radiances measured by High Resolution Infrared Radiation Sounder (HIRS) on board of the National Oceanic and Atmospheric Administration satellite (NOAA). The implementation of the ANN in the context of the satellite operational system in the National Institute for Space Research is also proposed. A perceptron multilayer network (MLP) trained with the error backpropagation algorithm is evaluated, through comparison with radiosonde data observed during two fields campaign carried out at distinct periods and places over South America. The temperature bias is similar in both experimental campaigns. The ANN produces quite well the spatial distribution temperature, mainly for those levels close to surface over clear sky scene. Overall, the ANN shows to be an easy and fast tool to be used to retrieve operationally vertical profiles based on satellite information.

Introduction

Atmospheric profiles estimated from satellite data have become very important to weather analyses and to numerical weather prediction modeling through data assimilation process. The vertical structure of atmospheric temperature and humidity is one of the main factors that determine the weather and climate conditions. Therefore knowledge of these variables is essential to monitor and modeling of the atmosphere. Sensors aboard weather balloons are launched routinely around the world by altitude meteorological stations (radiosonde) in order to observe these structures. However, analysis of the spatial distribution of these stations shows the contrast of data availability between different regions. Oceans and remote continental areas, such as deserts and forests, have no radiosonde data, while countries like the United States and Europe have a relatively dense network of altitude stations.

As an additional information to the radiosonde, sensors aboard weather satellites - sounders - offer opportunity to infer the thermodynamic structure of the atmosphere, especially for the Southern Hemisphere where there is a low number of radiosondes. The main advantage of the technique with respect to radiosonde is temporal resolution and spatial coverage. Another sounding advantage is the possibility of combining several polar orbit satellites (low orbit), with the same instrumentation. For instance, NOAA and METOP satellites series have both the ATOVS system - main sounder. Information from three satellites with onboard ATOVS allows obtaining profiles every 6 hours with spatial coverage of approximately 70% of the globe.

The development and improvement of retrieval schemes for inference of vertical atmospheric structure in terms of temperature, humidity and molecular species concentration is essential in Numerical Weather Prediction [1]. This is especially important considering the present and future hyperspectral technologies availability. Several methodologies have been developed for the recovery of atmospheric profiles from sensors onboard satellites; among them stand physical methods [2, 3]. However, these methods require a good initial condition besides the direct model, and statistical methods based on regression analysis [3, 4]. Compared with physical models, statistical models are simpler and more robust in the presence of noise. Moreover, some statistical techniques found in the literature, for example, the technique of Artificial Neural Networks (ANN), takes into consideration the nonlinearity of the problem.

Within this context, this paper presents an application of Artificial Neural Network technique to retrieve information about vertical profiles of temperature from data brightness temperature of the sensor HIRS/ATOVS onboard NOAA satellites. Additionally, integration of the technique on the operating system for the reception and preprocessing of satellite data is also presented in the context of the center of weather forecast.

1. Methodology

This section is divided in two parts. Initially an operational system to retrieve the thermodynamical profiles is proposed. Secondly, the data used in the system are presented.

1.1. A Proposed Operational System Using ANN to Retrieve Vertical Temperature Profile

Figure 1 shows a proposed simplified framework for an end-to-end retrieval system using the different INPE (National Institute for Space Research) capabilities mainly in terms of data availability and satellite processing. The system could be divided in four stages.

At the top of this framework, *satellite reception and pre-processing* (*stages 1 and 2*) are in charge of producing the radiance data, which will feed the so-called *retrieval scheme (stage 3)*, and then display at the format of the user application (*stage 4*). More details on each stage are given below.

INPE operates the regional reception of the NOAA polar-orbiting satellites data (stage 1). The local NOAA data are acquired in real-time via the satellite's digital High Resolution Picture Transmission broadcast (HRPT stations). As shown on the map placed at the first stage, this reception covers a wide region over South America and Atlantic Ocean.

The *pre-processing* stage aims to convert the satellite raw-binary data into physical – calibrated –navigated quantities (radiances or brightness temperature, level L1D) using the software AAPP [5]. An example of the calibrated brightness temperature of channel 7 is shown in the map placed at second stage, which is used as input to the *retrieval scheme* (stage 3).

In this stage, satellite brightness temperature data (L1D) are read and written in ascii file format for different latitudes and longitudes. These data are used to activate the ANN. The outputs are latitude, longitude and air temperature for 43 levels in ascii file format. There are several ANN different architectures. Here an enhanced ANN based on Multilayer Perceptron (MLP) with backpropagation learning is employed.

Finally, at left bottom end of the framework, the data is displayed according to the user application requirement (*stage 4*). In the case shown, the spatial distribution of air temperature at 920 hPa and vertical profile are exemplified as a display of results usually required by the meteorologists. Binary data is also required for numerical weather forecast modelers.

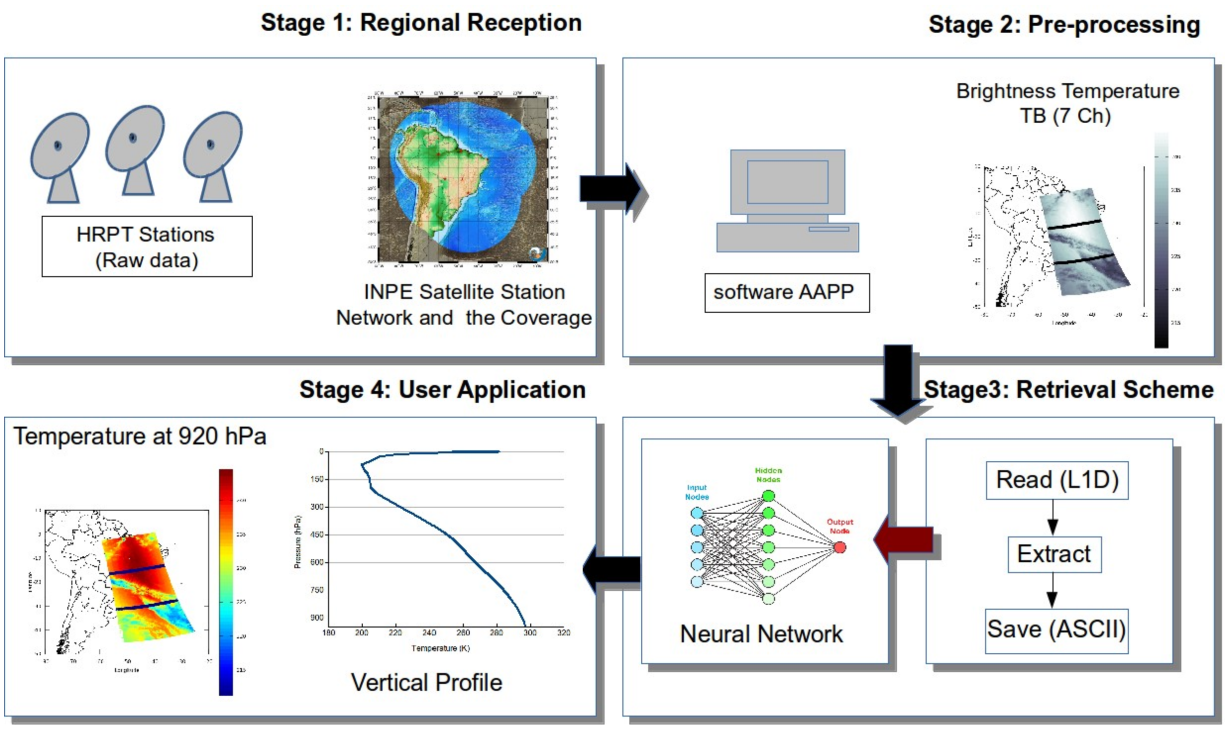

Fig. 1. A simplified framework for an end-to-end retrieval system.

1.2. The Multilayer Perceptron

The multilayer Perceptron (MLP) network is one of the networks most used in the literature and have been successfully applied to solve many complex problems through their training of supervised form with a very popular algorithm known as error backpropagation [6, 7]. The algorithm provides numerical efficiency and stability of statistical methods, while achieving accuracy comparable of the physical models [8]. MLP presents a much larger computational power than networks without intermediate layers, since they have the capability to handle data that are not linearly separable [9, 10]. Advantages of using this technique are: tolerance to noisy data, the ability to adapt to different regions and low computational cost (after training). Two different phases can be distinguished while using an ANN: the training phase (learning process), and the run phase (activation of the network).

The percetron network has an input layer, one or more hidden layers, and an output layer. The training algorithm, error backpropagation learning, consists of two steps through the different layers of the network: a step forward (the propagation), and a step back (the back-propagation) (figure 2). Firstly, the input signal propagates forward, layer by layer until a set of outputs is obtained in the last layer. In the first hidden layer, each input unit is multiplied by a weight, corresponding to each neuron. The number of neurons in the hidden layer varies with the application. In the following layers, the same process is repeated, with the input of next layer being the output of previous.

During the propagation process, the synaptic weights are adjusted according to a error correction rule. The network response is subtracted from a desired response (target) to produce an error signal. This signal is then propagated back through the network against the direction of synaptic connections known as backpropagation.

Once trained, the weights are fixed and the network can be presented to new inputs for which it calculates the corresponding outputs, based on what it has learned. Data for network training can be obtained through experiments (observations) or using a mathematical model (or direct model). For the latter case, a noise is added to the signal to simulate the brightness temperature from a satellite sensor. The solution of the forward problem is used to calculate the radiances of different channels of a particular sensor on board satellite using atmospheric profiles as input. More details in using direct forward model can be found in [1, 11].

The perceptron network used in this study has 12 layers hidden in the training phase and in the phase activation. The activation functions of the two phases are nonlinear (logistic sigmoid). The output of the neural network is a vector with 43 values corresponding to temperatures at 43 different heights of the atmosphere, each of which corresponds to a pressure level.

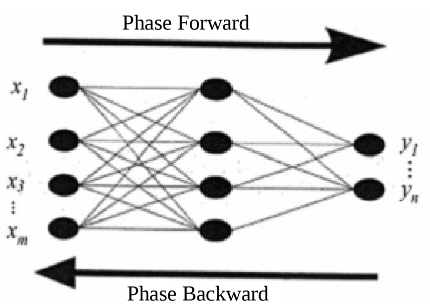

Fig. 2. Processing flow of the algorithm of the error backpropagation [7].

1.3. Data

The neural network was trained with a set of 646 randomly selected temperature profiles from the TIGR (TOVS Initial Guess Retrieval) database [11], using backpropagation algorithm – as mentioned before. There are 1761 profiles in the database TIGR. A reduced number of profiles were selected to avoid the overtraining. From these profiles, radiances related to the first seven channels sensor HIRS/2 (NOAA-14) were calculated – these bands are associated with the absorption band of CO_2. A Gaussian noise was added, for experimental data emulation:

$$\tilde{I} = I_{exact} + \sigma\mu \qquad (1)$$

where μ is a random variable with zero mean and unit variance from a Gaussian distribution, and σ is the level of noise. In this article, the experiments were corrupted with 5% of noise. The computed radiances were converted into brightness temperatures by inversion of the Planck's equation with transmittance available in the literature [12] – for more details see [13].

For the activation phase, the inversion by ANN used data from the sensor HIRS/3 Sounder onboard of the NOAA-18. It measures radiances in the visible spectral range (1 channel), and infrared (19 channels), with a 10 km spatial resolution on nadir. However, only seven channels were utilized, representing the main weight functions for the atmospheric layers. Data from this instrument are useful for the inference of temperature and humidity profiles, land surface temperature and sea. This is one of the first instruments aboard the NOAA series of polar-orbiting satellites (from 1978, this means over 30 years). The passages correspond to 06 and 18 GMT on South America during the months of June/2008 and December/2012.

The ANN outputs were compared with the respective information from radiosonde at the same time when the satellite was traveling over the northern and southern Brazil. Data sets for radiosonde observation from two projects were used: Chuva (http://chuvaproject.cptec.inpe.br/), and MiniBarca (http://www.master.iag.usp.br/lba/index_mb.php) – Figure 3. In the first project, the campaigns were held in the city of Santa Maria (Rio Grande do Sul state, Brazil) on three different locations at the same city. The campaigns of second project were conducted in Belém (Pará state), Manaus (Amazonas state), and Rio Branco (Acre state), all Brazilian states. The profiles of the radiosonde were linearly interpolated to the same levels of the ANN outputs. The average deviation of the inversion results for each pressure level obtained with the neural network was calculated as:

$$Error = \frac{1}{N_P} \sum \left(T_i^{NeuralNetwork} - T_i^{radiossonde} \right) \quad (2)$$

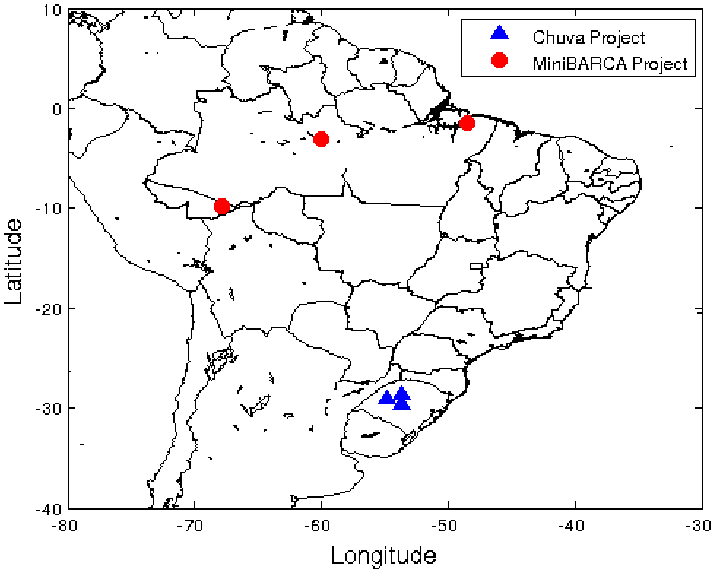

Fig. 3. Map showing Brazil and part of South America and radiosonde sites from Chuva and MiniBarca projects.

2. Results

Figure 4 shows the temperature field at 957 and 521 hPa associated to the passage of NOAA18 at 18:00UTC for two different data during the winter (15th June, 2008) and summer austral (4th December, 2012). Temperature varies spatially from 25ºC up to -80ºC for the same satellite passage. Negative and positive temperatures are related to cloudy and clear sky pixels, respectively. It is important to mention that negative values in Fig. 4 should be interpreted as the temperature on cloud top level instead at 957 hPa. This is because although IR channels used here (i.e., HIRS channels 1-7) have weight function centered at lower levels, they are highly sensitive to clouds. Clouds absorb IR radiation from lower levels and emit it approximately as blackbody. As their top temperatures are generally colder than lower levels, it is observed negative temperature values in Fig.3. Therefore, as expected for cloudy contaminated scene, the use of IR window channels seems to retrieve ineffectively atmospheric levels below the cloud top. The ANN seems to produce the 957 hPa spatial distribution over clear sky scene. It is observed the temperature contrast over the continent between those two dates. Temperature at 957 hPa seems to be much higher on June 2008 than December 2012. The area coverage difference between two dates is because INPE has reception stations in different places in order to broadcast more than one satellite passage over Brazil. The figures 4(a,c) are associated to the satellite antenna located at Sao Paulo State (Cachoeira Paulista, SP) close to the Atlantic Ocean, while the figures 4(b,d) covering part of the Brazilian Amazon and to Argentina is observed by antenna placed on interior of Brazil (Cuiabá, MT).

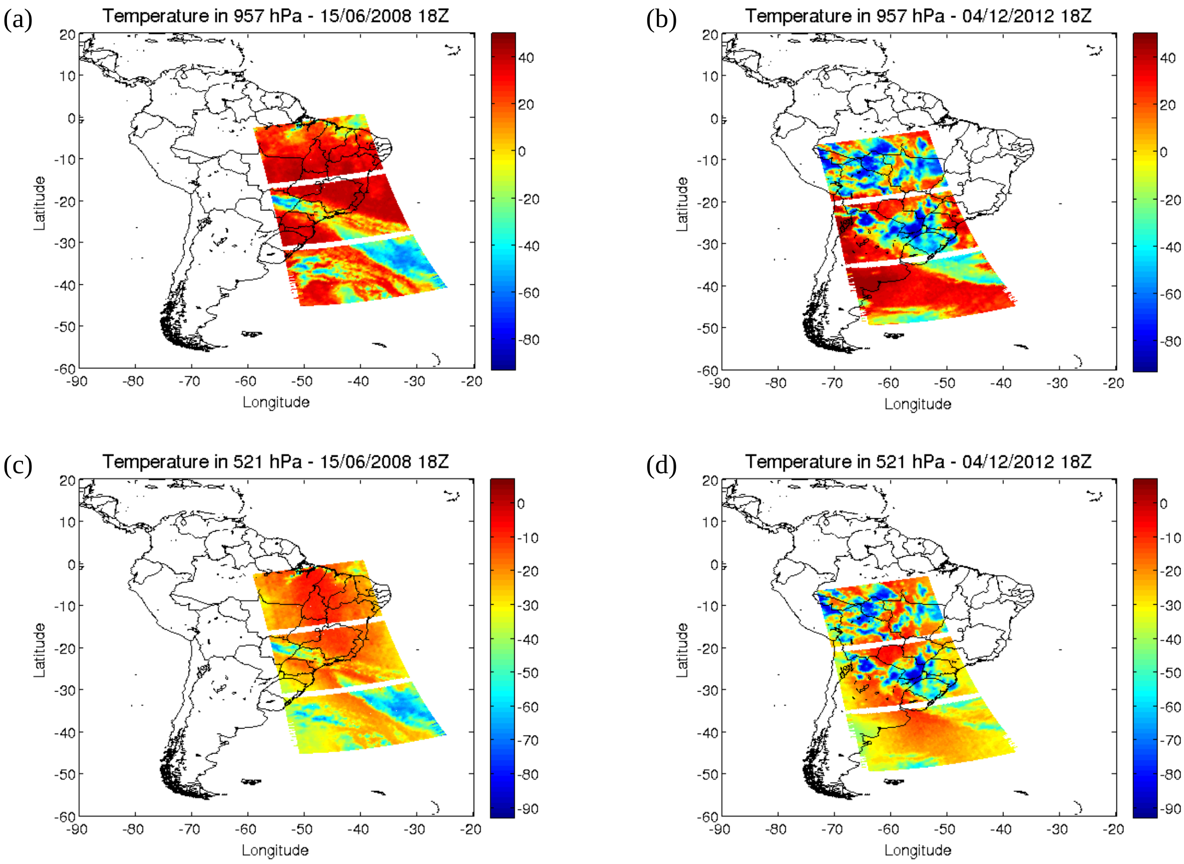

Figure 4. Spatial distribution of air temperature at 957 (a, b) and 521 hPa (c, d) retrieved based on ANN scheme and radiances from sensor HIR/NOAA18 for two different data during the winter (15th. June, 2008) and summer austral (4th December, 2012).

In order to determine the ANN performance, the retrieved temperature profiles were evaluated using radiosonde observation available from two campaigns. Observational data were selected on the regions (image pixels) not contaminated by clouds. There were available 10 and 9 observed profiles available from the Mini-barca and Chuva Project campaigns, respectively. Figure 5 shows the vertical profiles estimation obtained by ANN and by IAPP package [14] for two different regions: Minibarca and Chuva Projects (equatorial and sub-tropical zones – see figure 3). For both regions, the expected vertical profiles is followed: the temperatures decreases with the high up to the tropopause, increasing after that. Over the equatorial region, a better estimation was computed by IAPP scheme for whole troposphere. On the other hand, the ANN presented a better estimation close to the surface on the sub-tropical zone (see figure 5b). The ANN learning process was execute considering only 7 channels. The upper part of the troposphere is better represented by other channels, and they were not used for ANN trainning. For the IAPP,all 19 channels are considered, and there is a good estimation for the firstguest. Therefore, ANN temperatures retrievals above 800 hPa could be explained mainly due to other channels of the HIRS sounder not used, in which they are more appropriated at higher levels.

How were discussed in the section 1.3, the computed radiances were converted into brightness temperatures by inversion of the Planck’s equation. Better results also could be found changing the model direct for radiative transfer code, for example, RTTOV code (http://research.metoffice.gov.uk/research/interproj/nwpsaf/rtm/rttov_description.html).

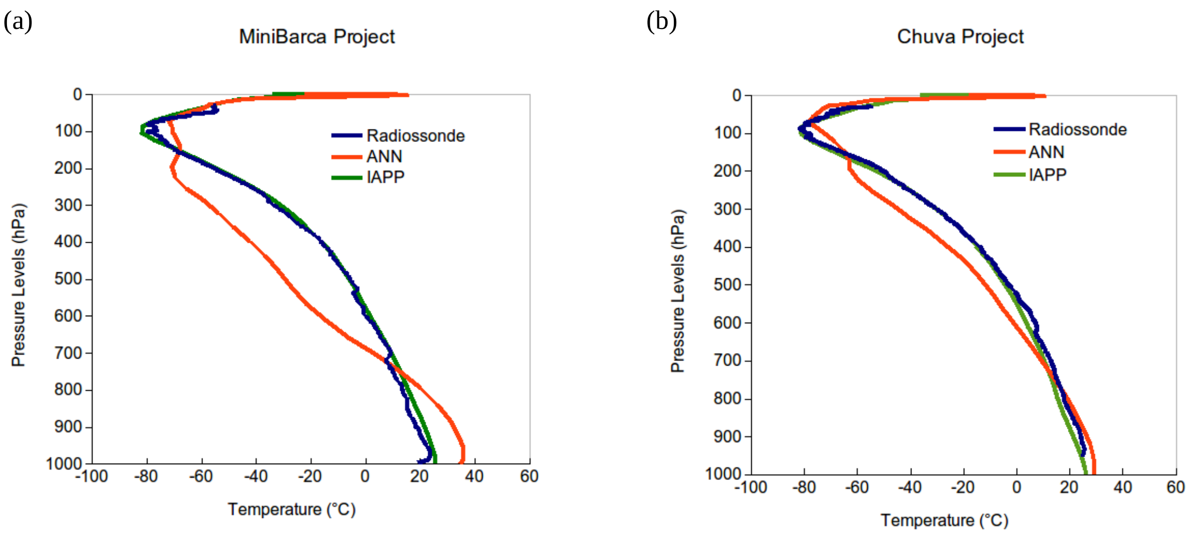

Fig. 5. Vertical profiles comparison among observation vs inversions (by ANN and IAPP package): (a) MiniBarca project, (b) Chuva Project.

3. Final Remarks and Conclusions

This paper presents an application of Artificial Neural Network technique to retrieve information from vertical profiles of temperature from data brightness temperature of sensor HIRS/ATOVS onboard NOAA satellites. These profiles are very important to weather analyses and to numerical weather prediction modeling through data assimilation process. In this context, estimated atmospheric profiles were compared with radiosonde data observed during two fields campaign. The radiosonde data were obtained at distinct periods and places over South America. The ANN scheme shows have higher accuracy at the lower level, were the mean bias (retrieval and observation) were lower than 5 ^{o} C.

Since clouds are generally opaque to the IR radiation that comes from lower levels, making the use of satellite's IR window channels information ineffective to retrieve atmospheric levels below the cloud top. A strategy to deal under cloudy conditions has been recently proposed by [15] (see also [16]). In such approach, the vertical profiles are estimated on two steps: firstly a *regular* inversion procedure (as presented in this paper) for the atmosphere over the top of the cloud, and secondly estimating the incoming radiation for the cloud bottom. From this estimated radiation, the vertical profile is identified from the surface up to the bottom of the cloud, using *standard* inversion schemes – as shown in this article. ANN's are used for solving both inverse problems.

The ANN shows to be an easy and fast tool to be used to retrieve vertical profiles based on satellite information. This is mainly true considering that the new and future sounding sensors on board of satellite (i.e. IASI, AIRS, CRIs etc.) will applied sophisticated techniques based on hyper-spectral observations. This techniques will allow that targets from surface and atmosphere could be observed by thousands spectral channels. In this context, ANN seems to offer the needs required by hyper-spectral observations, since it is easy to implement and, most import, it is able to extract the main patterns and detect trends that will be available by the many channels.

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