ESTIMATION OF ATMOSPHERIC TEMPERATURE AND HUMIDITY PROFILES FROM MODIS AND RADIOSOND DATA USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

The aim of this study is to test the quality of the neural network for retrieving the temperature and humidity by comparison with the radiosond values and a linear regression method. Remote sensed images give useful information about the atmosphere. In this article, MODIS data is used to retrieve temperature and humidity profiles of the atmosphere. Two methods of linear regression and artificial neural network are used to retrieve the temperature and humidity profiles. A multilayer feed-forward neural network is tested to estimate the desired geophysical profiles. Retrievals are validated by comparison with coincident radiosond profiles.

1. INTRODUCTION

Remote sensing of the atmosphere is nowadays carried out by means of very sophisticated sensors, using both new and broader wavelength regions, and measuring with better frequency resolution and lower noise. As a consequence, larger amounts of data have to be efficiently processed in order to optimize the retrieval performance (Del Fratea et al., 2005).

A remote measurement of the atmosphere from space with high spectral resolution can give a large amount of information about the atmosphere (Gribanov and Zakharov, 2004)

So far, different retrieval algorithms were developed to retrieve atmospheric profiles. All approaches can be divided into linear and nonlinear ones (Blackwell, 2005). In this article, two statistical techniques for retrieving temperature and humidity of atmosphere (profiles) from data of passive remote sensing are proposed.

We consider the retrieval of atmospheric temperature and humidity profiles (quantity as a function of altitude) from radiance measurements of MODIS sensor. A multilayer feed-forward neural network (NN) is used to estimate the desired geophysical profiles. The derivation of particular rules or a priori statistical information to be processed is not needed in this approach. NN establish the inverse mapping and the input–output discriminant relations on the base of data presented to them during the learning phase. Once the training process is completed, the network is able to give the new estimations in real time which can be very useful for many applications. To prevent the inversion algorithm from depending on climatological information also regularization techniques can be considered (Richards, 2005).

Selecting the inputs to the network, on the base of the effectiveness of their information content in estimating the output, eliminates unnecessary or misleading inputs that may confuse the network. Minimizing them while avoiding significant loss of information, affects positively the NN mapping ability and computational efficiency.

In this article, we first review the physics of spaceborne atmospheric remote sensing. Then we review used observation data contained in both MODIS and radiosond data. Next, we discuss using a neural network for estimating temperature and humidity profiles, and present performance analysing comparing the NN algorithm to the radiosonde values and a linear regression method and then we review multilayer feed-forward neural networks for geophysical parameter retrieval from spectral measurements and we give an overview of the network parameters used in this work.

2. SPACEBORN ATMOSPHERIC REMOTE SENSING

Figure 1 is showing a typical measurement scenario for spaceborne atmospheric remote sensing. A sensor measures upwelling spectral radiance (intensity as a function of frequency) at various incidence angles. The sensor data are usually calibrated to remove measurement artifacts such as gain drift, nonlinearities, and noise (Blackwell, 2005).

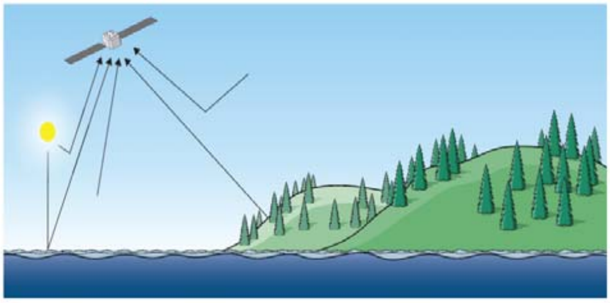

Figure1. Typical measurement scenario for spaceborne atmospheric remote sensing.

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The spectral radiances measured by the sensor are related to geophysical quantities, such as the vertical temperature profile of the atmosphere. An appropriate retrieval algorithm is necessary to convert these radiances into a geophysical quantity of interest (Blackwell, 2005).

The radiative transfer equation describing the radiation intensity observed at altitude L, viewing angle θ, and frequency ν can be formulated by including the emitted atmospheric contribution, the reflected atmospheric and cosmic contributions, and the radiance emitted by the surface as follows (Staelin, 1969):

$$\begin{aligned} R_\nu(L) = &\int_0^L \kappa_\nu \zeta_\nu [T(z)] e^{a(z)} \sec\theta dz \\ &+\rho_\nu e^{-\tau^* \sec\theta} \int_0^L \kappa_\nu \zeta_\nu [T(z)] e^{\beta(z)} \sec\theta dz \\ &+\rho_\nu e^{-2\tau^* \sec\theta} \xi_\nu(T_c) \\ &+\varepsilon_\nu e^{-\tau^* \sec\theta} \xi_\nu(T_s), \end{aligned} \tag{1}$$

where ε_ν is the surface emissivity, ρ_ν is the surface re-flectivity, $\kappa_\nu(z)$ is the atmospheric absorption coefficient, τ^* is the atmospheric zenith opacity, *T(z)* is the temperature profile, T_s is the surface temperature, T_c is the cosmic background temperature (2.736 ± 0.017 K), and

$$\begin{aligned} \alpha(z) &= -\int_z^L \sec\theta \ \kappa_\nu(z')dz' \\ \beta(z) &= -\int_0^z \sec\theta \ \kappa_\nu(z')dz'. \end{aligned} \tag{2}$$

$\xi_\nu(T)$ is the radiance intensity emitted by a blackbody at temperature *T*, which is given by the Planck equation:

$$\xi_\nu(T) = \frac{h\nu^3}{c^2} \frac{1}{e^{h\nu/kT} - 1} \ W.m^{-2}.ster^{-1}.Hz^{-1}. \tag{3}$$

The first term in Equation 1 can be recast in terms of a transmittance function $T_\nu(z)$

$$R_\nu(L) = \int_0^L \xi_\nu[T(z)] \left(\frac{dT_\nu(z)}{dz}\right) dz. \tag{4}$$

The derivative of the transmittance function with respect to altitude is often called the temperature weighting function

$$W_\nu(z) \stackrel{\Delta}{=} \frac{dT_\nu(z)}{dz}, \tag{5}$$

and gives the relative contribution of the radiance emanating from each altitude.

3. OBSERVATION DATA

3.1 MODIS Data

The brightness temperature (*Tb*) is a measure of the intensity of thermal radiation given out by an object. This measure is in units of temperature, because it is correlated with the intensity of radiation and the physical temperature of the radioactive body.

The first Moderate Resolution Imaging Spectroradiometer (MODIS) was launched in December 1999 on the polar orbiting NASA Earth Observing System (EOS) Terra satellite and the second MODIS was launched on the polar orbiting Aqua satellite in May 2002. Each MODIS acquires daily global data in 36 spectral bands—29 with 1 km, 5 with 500 m and 2 with 250 m nadir pixels (Salomonson et al., 2006).

The Terra satellite was launched for global change research purposes. Terra's scientific instruments are used to provide atmospheric temperature and humidity profiles, clouds, precipitation and radiative balance; terrestrial snow and sea ice; sea surface temperature and ocean productivity; soil moisture; improvement of numerical weather prediction; monitoring of terrestrial and marine ecosystem dynamics (Cintra and Silva, 2006).

Most of channels that are opaque, due to atmospheric absorption, are referred to as sounding channels, while channels in which the atmosphere has little absorption are called window channels. Observations in the sounding channels are sensitive to atmospheric temperature and constituent profiles and can be used to determine these parameters (Salomonson et al., 2006). 5 spectral Bands employed in this article have been listed in the table 1.

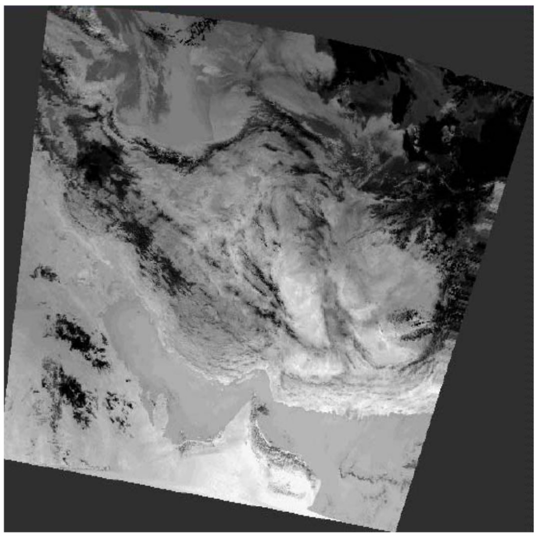

Figure2. Iran Image from MODIS Sensor on June 24, 2004

Sensor	Band (Bandwidth µm)
MODIS	23 (4.02 – 4.08)
	24 (4.433 – 4.498)
	25 (4.482 – 4.549)
	31 (10.78 – 11.28)
	32 (11.77 – 12.27)

Table 1. Characteristics of used MODIS sounding channels to retrieval atmosphere profiles

In this paper, we used the brightness temperature (*Tb*) from MODIS sensor as in Table 1. Therefore, in order to estimate atmospheric state from MODIS data, first we should measure brightness temperature using above Channels. These data were collected from the satellite passages at experimental sites of 00 and 12 GMT.

3.2 Radiosond Data

Radiosond data were acquired at a few meteorological stations in Iran. Within the framework of the Iranian Meteorological Organization (IRIMO), all observations were performed at “synoptic” hours: 0 and 12 h UTC. Therefore, the temperature and humidity profiles of radiosondes were also extracted during these stations. The sites of the experiment were: Mehrabad Airport of Tehran (35°41’ N, 51°19’E), Kermanshah (34°17’ N, 47°07’E), Shiraz (29°32’ N, 52°36’E) and Bandar Abbas (27°13’ N, 56°32’E).

The main objective of this project is to get atmospheric profiles of temperature and humidity from radiosond data and compare it to the profiles retrieved by using the MODIS sensor, at the same time.

4. METHODOLOGY

The objective of the geophysical parameter retrieval algorithm is to estimate the state of the atmosphere (represented by a parameter matrix X) given observations of spectral radiance (represented by a radiance matrix R). Note that the inverse model typically does not exist, as there are generally an infinite number of atmospheric states that could give rise to a particular radiance measurement.

There are generally two approaches to this retrieval problem. The first approach, called the *variational approach*, uses a forward model (for example, the transmittance and radiative transfer models previously discussed) to calculate the sensor radiance that would be measured, given a specific atmospheric state. The second approach, called the *statistical*, or *regression-based, approach*, does not explicitly use the forward model to derive the estimate of the atmospheric state vector. Instead, an ensemble of radiance/state vector pairs is selected, and a statistical characterization [p(X), p(R), and p(X, R)] is sought. In practice, it is difficult to obtain these probability density functions directly from the data, thus alternative methods are often used. Two of these methods are linear least-squares estimation (LLSE), or linear regression, and nonlinear least-squares estimation (NLLSE). Neural networks are a special class of NLLSE, and are discussed later (Blackwell, 2005).

4.1 Linear Regression Approach for Temperature and Humidity

A method to estimate temperature and humidity of the atmosphere from *Tb* of satellites data is based on the statistical correlation. It considers the hypothesis that temperature and humidity, in a layer of the atmosphere, can be obtained through a linear combination of the MODIS channels (Lambrigsen, 2003). Thus, the temperature and humidity in the layer can be estimated by:

$$T(L) = a(L) + \sum_{i=1}^{n} b_i(L) T_b(\nu_i) \tag{6}$$

$$RH(L) = a(L) + \sum_{i=1}^{n} b_i(L) T_b(\nu_i) \tag{7}$$

Where n is the number of channels, *T(L)* and *RH(L)* are temperature and humidity in the layer, *a(L)* and $b_i(L)$ are regression coefficients of channels combinations, and $T_b(\nu_i)$ is the brightness temperature measured in frequency ν_i.
The layers were chosen so that each one represented the maximum of the weight function for the MODIS channels. The estimation of the regression coefficients in Equations (6) and (7) used radiosonde data launched in the experimental sites for all timetables.
This method was used as a reference in this work and the statistical results of this method will be used for comparison with the results of the NN.
The NN applications are still a challenge for meteorologist investigators. Though an NN provides a way to establish a non-linear relation of the characteristics of the meteorological phenomena, the wrapped physics is not possible to explain with precision, as does the method presented by Cintra and Silva (2006), that justifies the comparison of its results with the NN method.

4.2 Neural Network Approach for Temperature and Humidity

The use of multilayer feed-forward neural networks, such as the multilayer perceptron, to retrieve temperature profiles from spectral radiance measurements has been addressed by several investigators (Motteler et al., 1995; Butler et al., 1996; Blackwell, 2005). Neural network retrieval of moisture profiles from spectral data is relatively new, but follows the same methodology used to retrieve temperature.

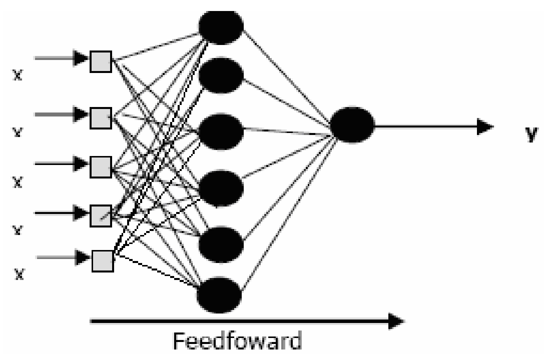

Figure3. Used Neural Network to retrieve atmospheric profiles

Feedforward neural network with the single hidden layer was trained for atmosphere profile retrieval. The training phase of the MLP required:

• *Input data* (x) of simulated and measured brightness temperatures in five channels of the MODIS (*Tb23*, *Tb24*, *Tb25*, *Tb31* and *Tb32*) at four sites of the experiment.

• *Output Data* (y) as the total temperature and humidity integrated from observations of profiles of radiosondes measured in the sites of the experiment from the surface (ho) up to the altitude in which there is the steam of water (h) in a unit column of dry air.

The training set was formed by the data of *Mehrabad airport* and *Kermanshah stations*. The *Tb* data were simulated by MODIS channels' data at all timetables. The temperature and humidity were based on all profiles measured in these sites.
The testing set was formed by the data from *Shiraz* and *Bandar Abbas stations* used like standards and radiosondes profiles at all timetables.
For the activation or generalization tests the *Tb* data of *Mehrabad airport* and *Kermanshah* measured by the channels of the MODIS and the calculated temperature and humidity of the radiosonde profiles at timetables of 00 GMT and 12 GMT were used. These data were also used in the reproduction of the results obtained by the linear regression method proposed in Lambrigsen (2003).

Several tests were done with different architectures; the one that provided better results was a two-layer MLP with six neurons in the hidden layer.

Considering a criterion of the least squared error and the best generalization did the choice of the number of neurons in the hidden layer. The ANN was trained with 20.000 "epochs", using the learning rate of 0.001.

The training obtained the least squared error of 0.0032, thus achieving a convergence with a good computational performance.

5. RESULTS

The results are punctual and they are presented in the temporal variability. The linear regression method was applied for checking the results using the same data.

Figures (figures 4 to 11) present the estimated temperature and humidity by the radiosondes and ANN for all the sites in this study. From the graphs one may infer a high correlation between the estimated temperature and humidity by the ANN and the radiosondes data.

The MODIS Brightness Temperatures were only measured at timetables of 00 UTC and 12 UTC. These data were acquired on the same days of satellite coverage of this site. Straight lines correspond to non-available data, that is, days with no observations. These figures present graphic line of the estimated atmosphere profiles by the regression model and the ANN method versus radiosondes. One may notice that the results of the ANN are closer to the radiosondes than the results of the linear regression method.

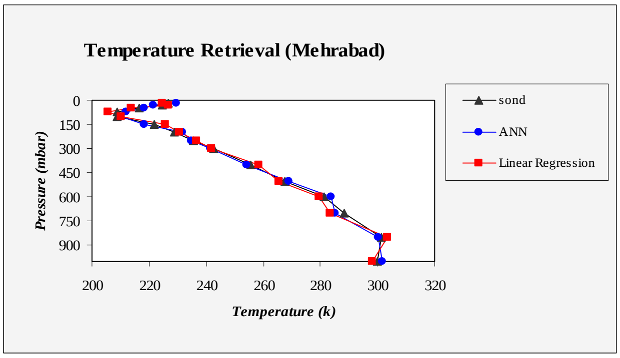

Figure 4. The temperature measured by radiosondes in *Mehrabad airport station* and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

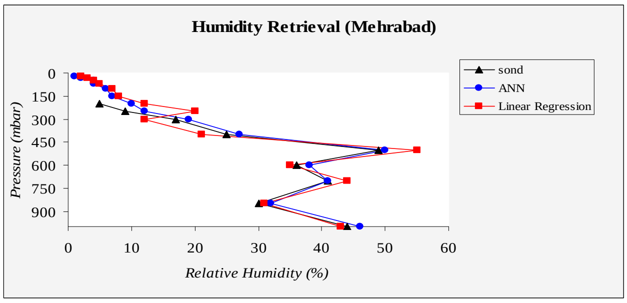

Figure 5. The humidity measured by radiosondes in Mehrabad airport station and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

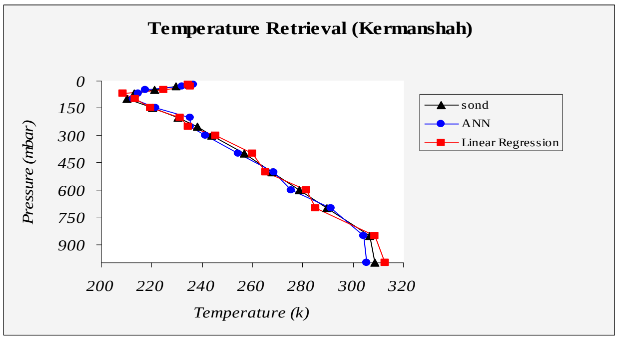

Figure 6. The temperature measured by radiosondes in Kermanshah station and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

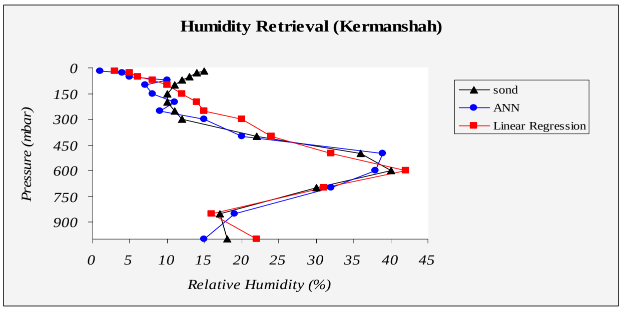

Figure 7. The humidity measured by radiosondes in Kermanshah station and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

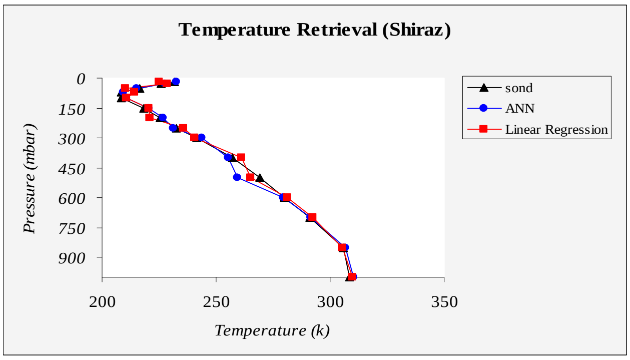

Figure 8. The temperature measured by radiosondes in *Shiraz Station* and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

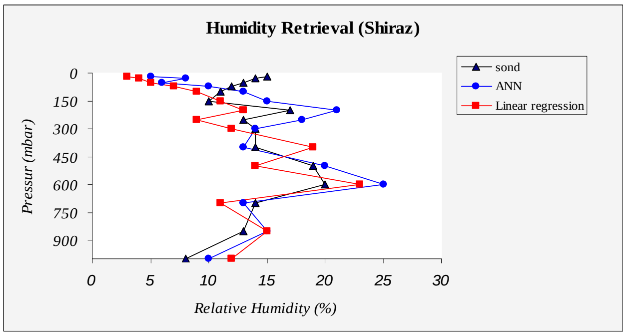

Figure 9. The humidity measured by radiosondes in Shiraz Station and the estimation provided by the (blue/dot) and the linear regression method (red/square).

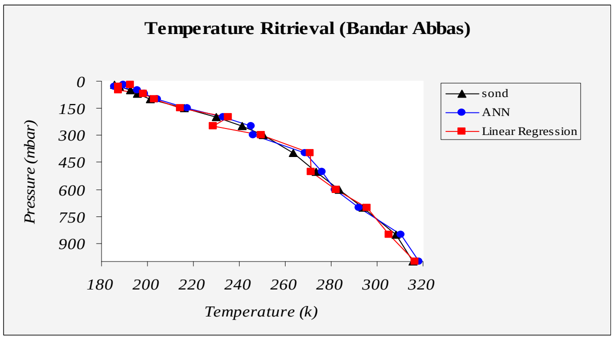

Figure 10. The temperature measured by radiosondes in Bandar Abbas Station and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square).

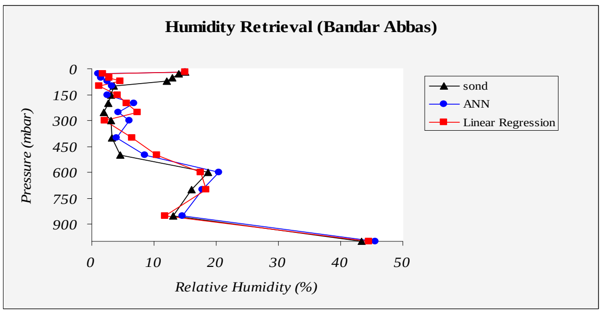

Figure 11. The humidity measured by radiosondes in Bandar Abbas Station and the estimation provided by the MLP (blue/dot) and the linear regression method (red/square)

MEAN	Radiosond		ANN		Regression	
Sites	T (k)	H (%)	T(k)	H(%)	T(k)	H(%)
Meh. Airport	247.2	28.4	247	19.9	247	20.1
Shiraz	248	14.7	248	13.7	248	11.1
Kermanshah	250	21.8	250	15.5	251	17.3
Bandar Abbas	242.6	10.3	244	9.89	243	9.91
RMSE	Radiosond		ANN		Regression	
Sites	T (k)	H (%)	T(k)	H(%)	T(k)	H(%)
Meh. Airport	32.73	15.6	32.4	17.4	32.3	17.9
Shiraz	34.78	3.6	34.3	5.6	35.5	5.42
Kermanshah	34.50	11.1	31.9	12.1	33.4	11.2
Bandar Abbas	45.49	12.5	45.4	13.2	44.2	11.4

Table.2. Estimated statistical parameters for three methods

The statistical results described in Table 2 present: the mean value of the radiosondes temperature and humidity values and output of the ANN. The rms error was in compared to the radiosondes and the ANN. The statistics of the regression method were redone for comparison with the ANN.

6. CONCLUSION

In this article, it is shown that the feedforward neural network with single hidden layer can be applied to the inverse problem of atmospheric state estimation. Fast retrieval of temperature profiles from MODIS radiance spectra with acceptable accuracy can be obtained. The method of this paper can be expanded to retrieval of water vapour, ozone and methane profiles from high resolution radiance spectra obtained by future sensors.

Based on the obtained results, one may conclude that artificial neural network method may satisfactorily estimate the atmospheric state to the variability. The estimation of the atmospheric state allows the direct connection of the brightness temperature to the quantity of temperature and humidity.

The observations of the radiosonde offer quite limited space coverage, especially in Iran, and then it is of the great importance to develop a method to estimate atmosphere profiles from satellite data. These estimated data will improve the limitations of meteorological observations of conventional stations.

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