Inverse Problems, Design and Optimization Symposium
Rio de Janeiro, Brazil, 2004

Atmospheric Temperature Retrieval using Non-linear Hopfield Neural Network

Vanessa C. de Viterbo[1], **João P. Braga**[1], **Élcio H. Shiguemori**[2]
José D. S. da Silva[2], **Haroldo F. de Campos Velho**[2]

[1] *Departamento de Química*
Universidade Federal de Minas Gerais – UFMG
Belo Horizonte, MG, Brazil
[vanessa, jpbraga]@oxigenio.qui.ufmg.br

[2]*Laboratório Associado de Computação Aplicada – LAC*
Instituto Nacional de Pesquisas Espaciais – INPE
São José dos Campos, SP, Brazil
[elcio,demisio,haroldo]@lac.inpe.br

Abstract. In this paper a non-linear formulation of Hopfield neural network is applied to the problem of retrieving vertical temperature profiles in the atmosphere from satellite data. This estimation is a key issue in meteorology, since it provides an important input for numerical weather prediction codes. This is a fundamental procedure in the Southern Hemisphere. This inversion process is a non-linear reconstruction, therefore a non-linear version of the standard Hopfield neural network is used to approach the problem. Results are compared with inversions obtained from regularized solutions.

INTRODUCTION

The retrieval of vertical temperature profiles in the atmosphere from the satellite data is a fundamental issue in numerical weather prediction models. It is particularly important in the Southern Hemisphere, where there are large areas uncovered by data collecting ground stations.

The resolution process requires the inversion of the radiative transfer equation (RTE) where the radiation is measured in different frequencies, related to the energy from different atmospheric layers. A nonlinear inversion procedure based on a Hopfield neural network (HNN) is used to approach the problem [1]. The advantage of using HNN is in the fact there is no need of set target data for training purposes. Inversion results for synthetic radiance data show good reconstructions, similar to the profiles obtained with regularized solutions to recover the temperature profile [2, 3].

THE NONLINEAR INVERSION METHOD

The relation between radiation intensity I from the Earth, for a given temperature T, is described by the by the Planck equation [4], if the system Earth-atmosphere can be considered as a black body. If this temperature is dependent on some other parameter, for example, the pressure p, one must consider the intensity of the radiation in a given interval, and the Planck function can be written as,

$$I_\lambda = \frac{8\pi hc}{\lambda^5} \int_{p_1}^{p_2} \left[\frac{1}{e^{hc/\lambda k_B T(p)} - 1} \right] \frac{\partial \Gamma}{\partial p} \, dp \quad (1)$$

in which $\partial\Gamma/\partial p$ is the variation of radiance against the pressure (p), and λ is the wavenumber of the radiation. For a given temperature profile, the computation of the radiance is a simple and well-posed problem, where the integral in equation (1) can be calculated by the Gauss-Legendre quadrature. This is the forward problem. On the other hand, the inverse problem consists on the computing of the temperature profile, $T(p)$, from the intensity of the radiation. The inverse problem is a more difficult task, because it represents a highly ill-conditioned Fredholm integral equation of the first kind. This is the problem to be considered at the present work.

An efficient new approach to handle nonlinear ill-posed problems has been presented recently [1]. This scheme is based on recurrent neural network method resulting in a set of differential equations, analogous to the Hopfield model [5].

Following the linear case, an energy function is defined as [5, 6],

$$E = \frac{1}{2}\sum_{j=1}^{N_\lambda} e_j^2 = \frac{1}{2}\sum_{j=1}^{N_\lambda}\left[\left(\sum_{i=1}^{N_p} K_{ij}\right) - I_j\right]^2 \qquad (2)$$

with $e_j \equiv (\sum_i K_{ij}) - I_j$. The quantities I_j and K_{ij} are, respectively, the radiation intensity, and the matrix (discrete) representation of the integral term in equation (1) (with scaling factor – not shown):

$$K_{ij} = \frac{8\pi hc/\lambda_i^5}{e^{hc/\lambda_i k_B T_j}} \left(\frac{\partial\Gamma}{\partial p}\right)_{p_j} w_j \qquad (3)$$

being p_j, w_j nodes and weights of the Gauss-Legendre quadrature. The number of experimental data (satellite channels) are represented by N_λ, and N_p stands for the size dimension (number of atmospheric layers). After the condition $dE/dt < 0$, imposed on (2), a set of differential equation are established [1]

$$\frac{du_i}{dt} = -\sum_{j=1}^{N_\lambda} \frac{\partial K_{ij}}{\partial T_i} e_j \qquad (4)$$

being the temperature T_i connected to the state variable by the following activation function:

$$T_i(u) = \tanh(u_i(t)) \ . \qquad (5)$$

Therefore, it is easy to get initial conditions for the system of differential equations (4) from a initial profile (first guess) of the atmospheric temperature.

RESULTS AND DISCUSSIONS

The inverse problem turns out to be highly underconstrained since, due to technological limitations, the number of observations corresponds to a fraction of the number of temperatures to be estimated. For instance, in the example presented hereafter, 40 temperature values are estimated from 7 radiance measurements (meaning $N_p = 40$, and $N_\lambda = 7$). In practice, operational inversion algorithms reduce the risk of being trapped in local minima by starting the iterative search process from an initial guess solution that is sufficiently close to the true profile.

Noiseless Data

In order to evaluate the Hopfield network using non-linear system, a simulation was performed to generate the radiance data using the integral radiative transfer equation (1), with a known temperature profile. Figure 1 shows the generated radiance data. The results obtained by the non-linear Hopfield neural network presented a very good agreement with the exact temperature profile (residual error of 0.3%) as can be seen in Figure 2.

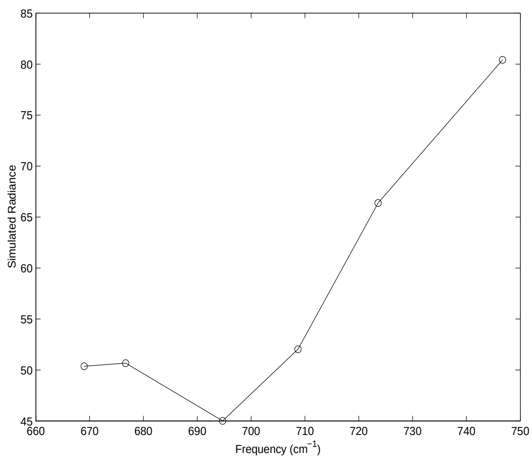

Figure 1: Simulated radiance satellite data.

An isothermal profile equal 280 K was established as a *priori* (initial guess) information for the system. The evolution of the neurons can be seen in Figure 3, which shows it learning along the time and convergence to it own state. In this present case noiseless radiances were considered.

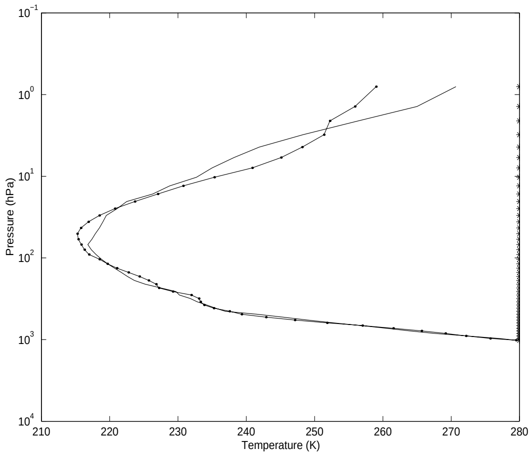

Figure 2: Inverted temperature profile, initial guess and ITTP-5 comparative profile.

The good performance of the Hopfield neural network to invert simulated radiance data to obtain the temperature profile in the atmosphere, suggests the use of radiance experimental data, as discussed later.

Experimental Data

The inversion for the atmospheric temperature is now compared with *in situ* radiosonde measurements, and using radiance data from the High Resolution Radiation Sounder (HIRS-2) of NOAA-14 satellite.

The results, as expected, presented a strong oscillation compared to the temperature profile computed by the ITTP-5 (International TOVS Processing Package - version 5), due to the noise in the

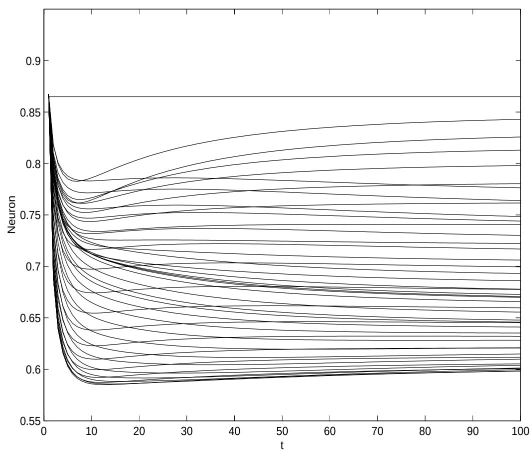

Figure 3: Neurons ($u_i(t)$) evolution with time.

observational radiances. For solving this oscillation problem – obtaining smoother results – a mobile average was applied. The final result showed a good agreement between the HNN retrievals and the radiosonde measurements for the range of 200-1000 hPa, as showed in Figure 4. A initial guess of 259 K was considered. The initial guess was defined by minor solution error for each isothermal temperature profile, Figure 5.

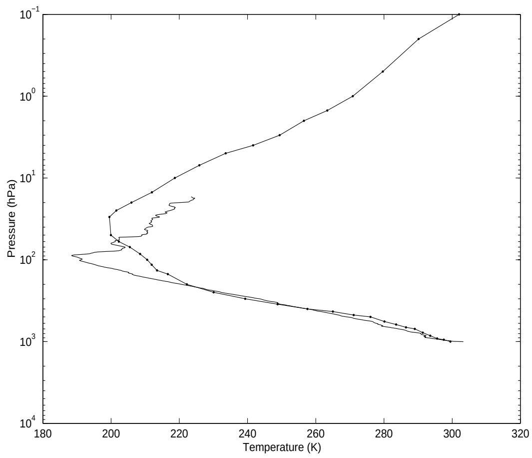

Figure 4: Inverted temperature profile for experimental data, initial guess and ITTP-5 comparative profile.

It should be pointed out that the retrieval from the ITTP-5 is dependent on the initial guess, poor reconstructions are obtained when a homogeneous initial profile is considered [2, 3]. However, the dependence of the final solution on a good choice of the initial guess represents a fundamental weakness of such algorithms, particularly in regions where less *a priori* information is available [7]. This is the main reason for considering alternative algorithms for this very important inverse problem.

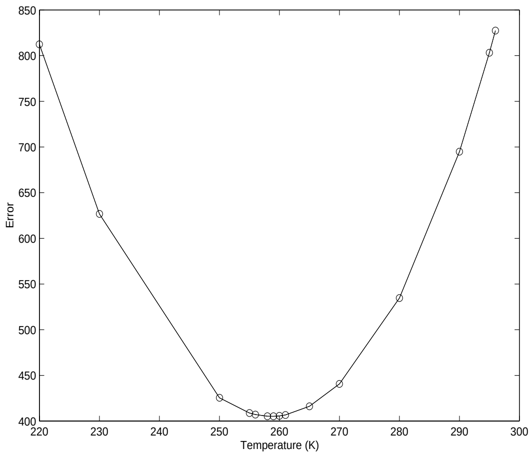

Figure 5: Solution error.

CONCLUSIONS

This paper presents results of retrieving vertical temperature profiles from satellite data. A non-linear Hopfield neural network is applied to approach the problem. The conducted experiments use simulated and real life satellite radiance data. The results are encouraging in the sense that the non-linear Hopfield neural network has achieved good inversions. However, the paper shows partial results and the proposed non-linear model needs to be validated on different data sets.

Acknowledgments

This work was supported by CNPq, Brazilian agency for research support.

REFERENCES

1. R. C. O. Sebastiao, N. H. T. Lemes, L. S. Virtuoso, J. P. Braga, Nonlinear global inversion of potential energy surfaces from the experimentally determined second virial coefficients, *Chemical Physics Letters*, **378**(3-4), p. 406 (2003).
2. F. M. Ramos, H. F. de Campos Velho, J. C. Carvalho, N. J. Ferreira, Novel Approaches on Entropic Regularization”, *Inverse Problems*, **15**(5), p.1139 (1999).
3. J. C. Carvalho, F. M. Ramos, N. J. Ferreira, H. F. de Campos Velho, Retrieval of Vertical Temperature Profiles in the Atmosphere, *3rd International Conference on Inverse Problems in Engineering* (3ICIPE), Proc. in CD-ROM, under paper code HT02, Port Ludlow, Washington, USA, June 13-18, UEF-ASME (2000).
4. K. N. Liou, *An introduction to atmospheric radiation*, Academic Press, 1982.
5. J. J. Hopfield, Neural networks and physical systems with emergent collective computational abilities, *Proceedings of the National Academy of Sciences, USA*, **79**, p.2554 (1982).
6. J. P. Braga, M. B. de Almeida, A. P. Braga, J. C. Belchior, Hopfield neural network model for calculating the potential energy function from second virial data, *Chemical Physics*, **260**, p.347 (2000).
7. A. Chedin, N. A. Scott, C. Wahiche, P. Moulnier, The improved initialization inversion method: a high resolution physical method for temperature retrievals from satellites of the TIROS-N series, *Journal of Climate and Applied Meteorology*, **2**4, pp.128 (1985).