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INVESTIGATION OF METHODOLOGIES FOR ATMOSPHERIC RETRIEVAL FOR THE CPTEC OPERATIONAL SYSTEM

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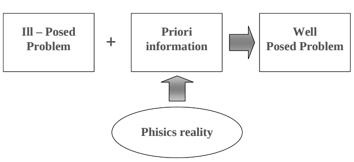
ATMOSPHERIC RETRIEVAL

The Center for Weather Forecasting and Climate Studies (CPTEC) is responsible for producing weather maps for the numerical prediction in Brazil. One key issue for numerical prediction is related to provide good estimation of the initial conditions for the atmospheric simulation code. One procedure consists of retrieving vertical atmospheric profiles for temperature and moisture profiles. The CPTEC operationally uses the Inversion Coupled with Imager (ICI-3) software in dynamic mode (CPTEC analysis) with the ATOVS/NOAA-16 system to supply such vertical profiles. However, CPTEC is also investigating new retrieval schemes that that have been developed at INPE. One of these schemes retrieves the profiles by means of a generalized least square problem, where a new regularization operator is employed. Such regularization operator is based on maximum entropy of second order [1, 2]. An Artificial Neural Network (ANN) is another scheme for retrieving the atmospheric profiles. The ANN is the Multi-layer Perceptron, with back propagation learning strategy [3]. The goal here is to compare these different methods, focusing on the operational procedures. The comparison is carried out by using two databases: TIGR and NESDISPR. About 500 profiles from the TIGR and 400 profiles from the NESDISPR, and associated radiances, are selected for testing the three strategies. The average error over profiles is used to perform the comparison among the inversion methodologies, and these analyses will be shown here.

ENTROPIC REGULARIZATION

Higher order of the entropic regularization represents a generalization of the standard MaxEnt regularization method, allowing a greater flexibility for introducing any prior information about the expected structure of the true physical model, or its derivatives, into the inversion procedure [1, 2].



$$\min\left(\left\| Kt - y \right\|_2^2 + \alpha\Omega[t]\right) \qquad (1)$$

Figure 1 – Regularization scheme

The Second Order entropic regularization:

$$\Omega(t) = -\sum_{q=1}^{N} s_q \ln(s_q)$$

$$s_q = \frac{t_{q+1} - 2t_q + t_{q-1} + 2(t_{\max} - t_{\min}) + \xi}{\sum_{q=1}^{N} t_q}$$

where ξ is a small parameter.

DATABASES

Two different database for temperature profiles were used: TIGR (Thermodynamic Initial Guess Retrieval) and NESDISPR worldwide climatological profile - a file created by the NOAA/NESDIS. The data sets were divided as: training, validation, and generalization data sets. The training and validation data are used for training the Artificial Neural Network , and the generalization data set are profiles not used during the training phase.

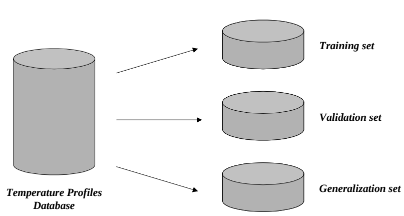


Figure 2 – Datasets

Table 1 - **TIGR**

Set	Profiles
Training	587
Validation	587
Generalization	587

Table 2 - **NESDISPR**

Set	Profiles
Training	405
Validation	400
Generalization	400

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) have become important tools for information processing. Properties of ANNs make them appropriate for application in pattern recognition, signal processing, image processing, financing, computer vision, and so on. There are several ANN different architectures. Here a Multilayer Perceptron (MLP) with backpropagation learning is employed.

$$y_k = \varphi\left(\sum_{j=1}^{n} w_{kj}\, x_j + b_k\right)$$

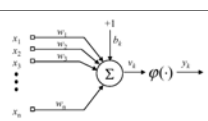


Figure 3 -Single Neuron

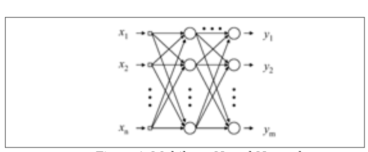


Figure 4 -Multilayer Neural Network

RETRIEVAL USING ANN

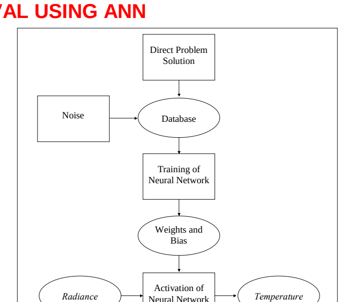


Figure 5 - Retrieval using ANN schema

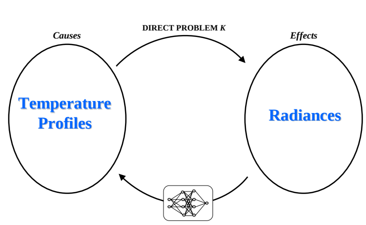


Figure 6 - Retrieval using ANN

ENTROPIC REGULARIZATION RESULTS

Entropic regularized solution is obtained by choosing the function t^* that minimizes the functional (1). The optimization problem is solved by the quasi-Newtonian optimizer routine from the NAG Fortran Library [4].

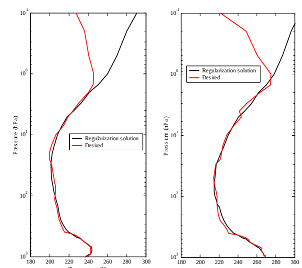


Figure 7 (a-b) Two examples results (TIGR database) obtained with second order entropic regularization.

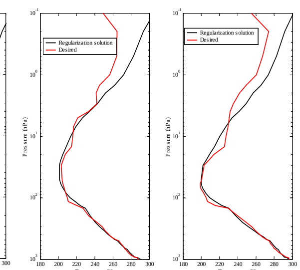


Figure 8 (a-b) Two examples results (NESDISPR) obtained with second order entropic regularization.

ANN RESULTS

The following figures present some examples of the ANN results. The Figure 9 (a-b) were obtained by the ANN trained with TIGR database. The Figure 10 (a-b) with the ANN trained with NESDISPR database.

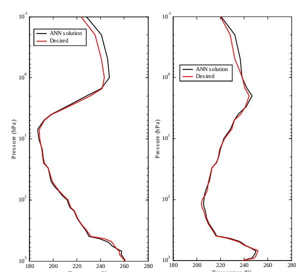


Figure 9 (a-b)Two examples of generalization test, obtained with the ANN trained with TIGR data sets.

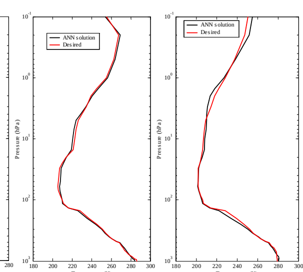


Figure 10 (a-b) Two examples of generalization test, obtained with the ANN trained with NESDISPR data sets.

The root mean-squared error of the generalization sets TIGR (587 profiles) and NESDISPR (400 profiles) are presented in Table 3, the errors are calculated in the Layer-1: 0.1 up to 15 hPa; Layer 2: 20 up to 70 hPa; Layer-3: 85 up to 200 hPa; Layer-4: 250 up to 475 hPa; Layer-5: 500 up to 1000 hPa;

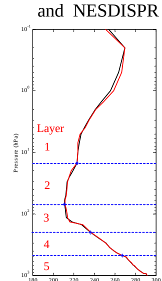


Figure 11 – Layers division

Both methodologies developed have produced good inversions, but ANN is much faster than entropic scheme to compute the retrievels.

Table 3 - Root mean-squared error of the generalization sets

Database	Neuron	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
TIGR	8	1.8161	0.9438	0.7043	0.7308	0.5153
NESDISPR	8	0.8836	0.6651	0.7714	0.3672	0.4849

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FAPESP CNPq WMO CAPES