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# DERIVING SURFACE SKIN TEMPERATURE AND ATMOSPHERIC PROFILES OF TEMPERATURE AND WATER VAPOR FROM HIRS MEASUREMENT USING A NEURAL NETWORK TECHNIQUE

Lei Shi and John J. Bates
NOAA/NESDIS/NCDC, Asheville, NC

## 1. INTRODUCTION

High Resolution Infrared Radiation Sounder (HIRS) is an operational infrared sounder aboard the National Oceanic and Atmospheric Administration (NOAA) polar orbiting satellites. It is a discrete stepping, line-scan instrument with 20 spectral channels. The channels are composed of twelve longwave channels, seven shortwave channels, and one visible channel. The HIRS channels are designed to provide measurement for deriving atmospheric temperature and water vapor profiles. In this study, the retrievals of temperature and water vapor profiles along with surface skin temperature retrieval from the HIRS measurement using a neural network technique are examined.

The retrieval algorithm facilitates the study of temperature and water vapor variations from long term HIRS observation. The NOAA series of satellites has operated with two primary sun-synchronous spacecrafts, one in a morning orbit and one in an afternoon orbit. At a given time, there are often two primary and sometimes additional secondary satellites having functional HIRS instruments. In order to use HIRS data for climate research, efforts have been made to correct the inter-satellite bias of the data (Wu et al., 1993; Bates et al, 1996). The work generated about twenty years of inter-satellite calibrated HIRS data that consist of cloud–cleared pentad brightness temperatures of HIRS channels 1-12. A multiple channel regression was developed for limb correction. Consistent quality control was applied through the entire data series (Jackson and Bates, 2001; Bates et al., 2001).

Several previous studies have successfully used neural network technique to derive atmospheric temperatures from satellite microwave sounders, e.g., Butler et al. (1996) retrieved atmospheric temperature based on the Defense Meteorological Satellite Program's Special Sensor Microwave Temperature Sounder data. Shi (2001) retrieved atmospheric temperature profiles from NOAA-15 Advanced Microwave Sounding Unit (AMSU) measurements, using neural networks applied to regional direct acquisition and global recorded AMSU-A data.

* Corresponding author address: Lei Shi, National Climatic Data Center, NOAA/NESDIS, Asheville, NC 28801; e-mail: lei.shi@noaa.gov

Similar structures of neural networks as used by Shi (2001) are applied in the current study to derive surface skin temperature and atmospheric profiles of temperature and water vapor from HIRS measurement. In the retrieval schemes, only channels 1-9 and 11-12 are considered. Through the NOAA satellite series, there have been several changes in the channel 10 central frequency. The channel 10 central frequency is 1225 $cm^{-1}$ on NOAA-6 through NOAA-10 and on NOAA-12, 797 $cm^{-1}$ on NOAA-11 and 14, and 802 $cm^{-1}$ on NOAA-15 and later satellites. Furthermore, there is a change of the HIRS channel 10 scan mirror coating on NOAA-9 and later satellites. To keep the consistency of long term retrieval, channel 10 is not considered in the input. HIRS channels 13 - 20 are excluded because of their shortwave and visible spectrums.

## 2. NEURAL NETWORK TRAINING

The neural network training dataset is based on a diverse sample of profiles simulated by the European Center for Medium-Range Weather Forecasts (ECMWF) system (Chevallier, 2001). The model profiles are generated by the ERA-40 assimilation system with the 3-dimensional variational scheme described by Courtier et al. (1998). The profiles are selected from the first and the 15$^{th}$ of each month between January 1992 and December 1993. The profiles are divided into seven groups differing by the total precipitable water vapor content of the profiles. About the same number of samples is extracted from each group, except for the group with the lowest precipitable water vapor content (0 to 0.5 $kg.m^{-2}$). For this group, twice as many profiles are extracted in consideration of the higher temperature variability from all types of situations from polar to tropical. The total sampled database consists of 13495 profiles in 60 vertical grids between the surface pressure and 0.1 hPa. Among many variables, the database includes temperature profile, specific humidity profile, surface skin temperature, ground surface pressure, etc.

To construct the neural network training dataset, the profiles are interpolated onto 35 pressure levels from 1000 to 0.1 hPa. Because the neural network training dataset requires values at each pressure level, the profiles with the surface pressure value less than 1000 hPa are excluded. The radiation transfer model MODTRAN is used to simulate the HIRS channel brightness temperatures of each profile. Garand et al. (2001) discussed intercomparison of HIRS and AMSU channel radiances derived from eighteen different radiative transfer models. Among the selected seven

HIRS channels (channels 2, 5, 9, 10, 11, 12, and 15) examined in the project, the standard deviations of MODTRAN simulated radiances are within 0.25 K for four of the channels, and within 7 K for the other three channels.

The HIRS channels 1-8 are located in the $CO_2$ absorption band which is temperature sensitive. The measurement assumes constant $CO_2$ concentration in the atmosphere. However, through the twenty years of the HIRS data series, the $CO_2$ concentration increased from 330 ppmv to 370 ppmv. The increase of $CO_2$ has an impact on the channel measurements. To account for the impact from the $CO_2$ increase, the MODTRAN is run at four $CO_2$ values of 320, 340, 360, and 380 ppmv. The simulated HIRS brightness temperatures are collocated with the input profiles and placed in the training dataset. The training data contain a total of 39912 collocated patterns.

Backpropagation neural networks are used in developing the retrieval scheme. A presentation of the backpropagation theory, architectures, and applications can be found in Chauvin and Rumelhart (1995). A backpropagation neural network is a computer model composed of individual processing elements called neurons. A network consists of multiple layers of neurons interconnected with other neurons in different layers. These layers are referred to as input layer, hidden layer, and output layer. Each layer is generally fully connected to the layers below and above.

## 3. RETRIEVALS

### *3.1 Temperature Profile*

Different backpropagation architectures with different numbers of layers and transfer functions are examined for the temperature profiles retrieval. A five-layer network, with one input layer, three hidden layers, and one output layer, is chosen based on the improved performance compared to four-layer and three-layer networks. It is found that using a hyperbolic tangent function to propagate to each of the three hidden layers and a logistic transfer function to propagate to the output layers gives the optimum network performance for the type of data studied. The definition of the hyperbolic tangent transfer function is

$$f(x) = \tanh(x), \tag{1}$$

and the definition of the logistic transfer function is

$$f(x) = \frac{1}{1+\exp(-x)}\ . \tag{2}$$

The numbers of neurons in the hidden layers are adjusted to optimize the performance.

Different channels are selected as input for different levels of the atmosphere. A number of six to eight channels with weighting functions peaking near the retrieval levels are selected as input variables. The input set also includes the $CO_2$ concentration to account for the effect of $CO_2$ increase through the twenty years of the HIRS data used for this study. The retrieval temperatures are obtained at 18 pressure levels, at 1000 hPa and every 50 hPa interval from 850 to 50 hPa.

Among the total of 39912 collocated patterns, 20% (7982 patterns) are randomly extracted to construct a testing set, and another 20% are randomly extracted and set aside as a validation set for later statistical studies. As a result, there are 23948 patterns remaining and they are kept in the learning set. A backpropagation network is trained by “supervised learning”. The network is presented with a series of pattern pairs, each consisting of an input pattern and an output pattern, in random order until predetermined convergence criteria are met. At this time the network presents the input elements in the testing set and retrieves the output elements. Then the retrieved output elements are compared with the output elements in the testing set, and the averaged root mean square (rms) errors of all the output elements are computed. The network parameters are saved if the averaged rms error is less than that computed previously. This process is repeated until no improvement is found for a specified number of test trials.

Using the saved network parameters, the retrievals corresponding to each input pattern in the validation set are calculated. The rms deviation is computed using the output pattern in the validation data set as truth data. Fig. 1 illustrates the resulting rms errors of the temperature profiles. The figure shows that for the atmospheric temperature profile retrieval, the rms errors are 1.5-2.4 C at the near-surface levels, about 1.3 C in the mid-troposphere, and 1.5-2.1 C around and above the tropopause. In recent years many different studies have used different methods to derive temperature and water vapor profiles from satellite sounder measurements. A retrieval scheme named Inversion Coupled with Imager (ICI) was developed by Lavanant et al. (1999) and used in a number of operational and research organizations (e.g., Carvalho et al., 2002 and Wu et al., 2002). Borbas et al. (2002) compared the ICI retrievals with the International ATOVS Processing Package (Li, et al., 2000). The rms values obtained in the present study show similar patterns as these studies using different retrieval methods. The larger rms values near the surface and tropopause are primarily due to the broader temperature variation ranges in these levels.

### 3.2 *Water Vapor Profile*

A similar retrieval technique is used to derive water vapor mixing ratio profiles. The input to the retrieval includes HIRS channels 2-8 and 11-12 and the $CO_2$ concentration. To build the neural network training dataset, the mixing ratio profiles are derived from the specific humidity and temperature profiles and collocated with the HIRS channel brightness temperatures simulated by the MODTRAN. The training dataset is also partitioned as learning, testing, and validation sets at 60%, 20%, and 20%. The water vapor mixing ratio values are retrieved at pressure levels from 1000 to 300 hPa.

Similarly, the network is trained by randomly presenting the input and output pairs from the learning set. When the predetermined convergence criteria are met, a mixing ratio retrieval is performed using the input data from the testing set. The retrieved elements are compared with the output elements in the testing set. The process is repeated and the network parameters that generated smallest averaged rms deviation among the comparisons are saved to build a computer model of the neural network.

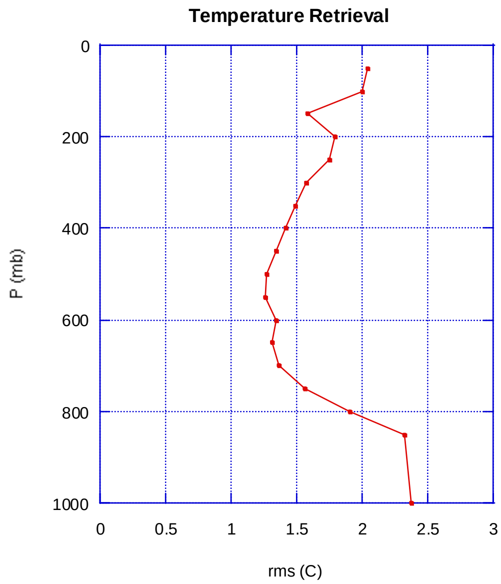


Fig. 1: The rms errors of temperature profile retrieval.

This neural network model is applied to the data in the validation dataset. The rms deviations of water vapor mixing ratio at all the levels are computed assuming the outputs in the validation dataset as truth data. The computed rms errors of the mixing ratio are shown in Fig. 2. The rms error at 1000 mb is 2.1 g/kg. The rms errors decrease steadily to 1.8 g/kg at 800 mb, 1.2 g/kg at 700 mb, 0.7 at 600 mb, and less than 0.4 g/kg above 500 mb. These rms values are typical compared with the studies using ICI retrievals (e.g., Carvalho et al., 2002 and Wu et al., 2002). The feature of largest rms values at the near-surface levels and decreasing values upward corresponds to the standard deviation feature of the water vapor mixing ratio dataset.

### *3.3 Surface Skin Temperature*

Each HIRS channel is examined for its contribution to the surface skin temperature retrieval. Sets of different neural network retrieval structures are built using different selections of HIRS channels. In each set the HIRS channels are added or removed one at a time to examine its impact to the retrieval. In each test the channel that has least contribution to the surface skin temperature is removed. It is found that selection of HIRS channels 4-8 and 10-11 gives the best retrieval result. The tropospheric channels (channels 1-3), the ozone channel (channel 9) and the mid-tropospheric water vapor channel (channel 12) are excluded due to their small correlation with the surface skin temperature. Exclusion of these channels reduces noise and results in a more stable retrieval scheme. The rms error of the surface skin temperature retrieval is approximately 0.7 C. The accuracy is better than the air temperature retrievals at the near-surface levels. The larger rms errors in the near-surface air temperatures are partly due to fact that the air temperatures are indirectly observed from space. It is estimated through the correlations with more directly observable quantities such as skin temperature or the mean temperature of a thick atmospheric layer.

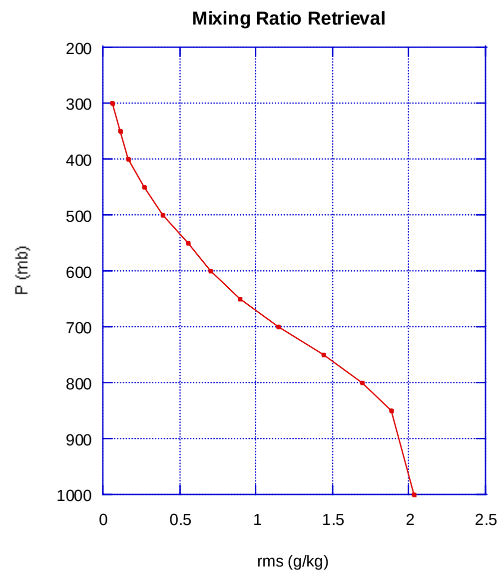


Fig. 2: The rms errors of water vapor mixing ratio profile retrieval.

## 4. CONCLUSION

Neural network models are found capable of connecting the nonlinear relation between HIRS channel measurements and atmospheric temperature and water vapor profiles along with surface skin temperature. Past studies that showed statistics on satellite temperature and water vapor profile retrievals mostly focused on regional scale (Carvalho et al., 2002 and Wu et al., 2002). These studies illustrated that for the temperature profile retrieval, the rms errors were around 1-3 C at the near-surface levels, 0.8-1.5 C at the mid levels, and 0.8-2 C near the tropopause. For the water vapor retrieval, the rms errors near the surface ranged from 0.7 g/kg to 3.5 g/kg, and decreased steadily towards upper atmosphere. The retrieval results obtained in the current study are within the rms error value ranges of the past studies.

The neural network training is performed based on a diverse global dataset. The training dataset includes data from all seasons, over both land and water surfaces. Such retrieval models provide a means to study long-term variability of global atmospheric temperature and water vapor from HIRS measurement.

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