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A combined natural orthogonal functions/neural network technique for the radiometric estimation of atmospheric profiles

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Abstract. An inversion technique is presented for retrieving vertical profiles of atmospheric temperature and vapor from the brightness temperatures measured by a ground-based multichannel microwave radiometer and the surface measurements of temperature and relative humidity. It combines a profile expansion over a complete set of natural orthogonal functions with a neural network which performs the estimate of the coefficients of the expansion itself. A simulation study has been carried out, and the algorithm has been tested by comparing its retrievals with those obtained by means of linear statistical inversion applied on the same data sets. The analysis has been limited to the case of profiles with clouds in order to test the ability of the neural network to face nonlinear problems. The technique has proven to be flexible, showing a good capability of exploiting information provided by other instruments, such as a laser ceilometer. A fault tolerance evaluation has also been considered, which showed interesting properties of robustness of the algorithm.

1. Introduction

The knowledge of profiles of atmospheric variables, such as temperature and water vapor, is relevant to several applications in the fields of meteorology, telecommunications, radio astronomy, air traffic safety, etc. Such profiles are commonly obtained from radiosonde measurements, launched every 12 hours from meteorological stations. However, it is often desired to have continuous measurements in real time, to follow the evolution of the state of the atmosphere.

Ground-based microwave radiometry has proven to be a powerful tool to perform continuous atmospheric sounding. An automatic profiler was operated from 1982 to 1992 at the National Oceanic and Atmospheric Administration Environmental Research Laboratory (NOAA/ERL) Wave Propagation Laboratory in Boulder, Colorado [*Hogg et al.*, 1983]. The profiles of temperature and water vapor are retrieved from the brightness temperatures measured by the six-channel microwave radiometer and from the surface measurements of pressure, temperature, and humidity, by means of linear statistical inversion [*Westwater*, 1972].

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To improve the accuracy of the profiles retrieved by ground-based radiometers, information provided by satellite-borne microwave radiometers is effective [*Westwater and Grody*, 1980; *Westwater et al.*, 1985]. The capabilities of each sensor are complemented by the other, and the overall error in the inversion is reduced.

Inversion algorithms based on the expansion of the atmospheric profiles in terms of a base of natural orthogonal functions (NOF) [*Obukhov*, 1960] have been proposed for the retrieval of profiles of temperature [*Askne et al.*, 1985] and humidity [*Del Frate et al.*, 1994]. A few functions describe each profile with a satisfactory level of accuracy, and therefore the retrieval process reduces to the estimate of the coefficients of the expansion.

Retrievals of temperature profiles using neural networks (NN) have been reported by *Churnside et al.* [1994]. Their neural network inversion of microwave radiometer data was nearly as good as an optimized statistical retrieval in terms of overall rms error, while in difficult cases, such as for strong temperature inversions, it better reproduced the essential features of the profiles.

Recently, *Han and Westwater* [1995] have developed a technique to derive profiles of water vapor, cloud liquid water, and temperature from an integrated system of ground-based sensors (dual-channel microwave radiometer, surface meteorological instruments, laser ceilometer, radio acoustic sounding system (RASS)). It is a combination of a classification technique and a linear statistical retrieval algorithm, which significantly improves the accuracy of water vapor profile retrievals, under cloudy conditions, compared to that using traditional retrieving systems.

In this paper we present a combined technique (NOF-NN) for the retrieval of atmospheric profiles of temperature and vapor. The profiles are expanded on a base of natural orthogonal functions, and the coefficients of the expansion are estimated with a neural network from the brightness temperatures measured by a seven-channel microwave radiometer. To test the intrinsic ability of neural networks to face nonlinear problems, we have restricted our analysis to the case of profiles with clouds, where the nonlinearities of the inversion problem are stronger. A performance evaluation of the algorithm has been made comparing the results obtained by our technique with those of a linear statistical inversion applied on the same data sets.

2. Simulation Setup

A simulation study has been carried out considering the brightness temperature of the atmosphere measured with a ground-based microwave radiometer aiming at zenith at the following seven frequencies: 22.235, 23.87, 31.65, 51.25, 52.85, 53.85, and 54.85 GHz. These values define the actual channels of a new-generation radiometer designed and developed under a European Space Agency (ESA) contract by Officine Galileo (Florence, Italy) [*Battistelli et al.*, 1995].

Two sets (training and evaluation) of profiles of temperature and water vapor have been statistically generated starting from the midlatitude summer standard atmosphere, by including realistic and physically acceptable humidity and temperature irregularities, ground-based inversions, and liquid clouds [*Schiavon et al.*, 1993]. Such sets of profiles can be made representative of particular locations by adjusting the relevant generating parameters. To better examine a more critical situation, we only considered profiles with clouds.

These synthetic atmospheric profiles have been used to compute the brightness temperatures, as would be measured at the various frequencies by the described radiometer, by using *Liebe et al.'s* [1993] millimeter-wave propagation model (MPM). To simulate noise in the radiometric channels, random fluctuations with 0.5-K standard deviation have been added to the brightness temperature data. The result obtained for the synthetic atmospheres has been confirmed for sets of actual radiosonde-measured profiles over various locations in Italy. Ground measurements of surface temperature and relative humidity have also been considered. A further optional piece of information is the height of the base of the cloud, which can be measured by a laser ceilometer. Its considered vertical resolution was 15 m.

3. The NOF-NN Algorithm

The NOF offer a valuable means of estimating the profiles of the relevant meteorological variables through the determination of a fairly compact set of coefficients [*Obukhov*, 1960]. The generic atmospheric quantity $F(z)$ (temperature or vapor), discretized in N height levels, can be expressed through the following equation:

$$F(z_i) = \langle F(z_i)\rangle + F'(z_i) \quad i = 1, 2, \ldots, N \quad (1)$$

where $\langle F(z_i)\rangle$ represents the a priori information contained in the mean climatological profile, and $F'(z_i)$, which has zero mean, is the deviation from $\langle F(z_i)\rangle$. The covariance matrix $[B]$ associated to the unknown vector $[F']$ (of elements $F'(z_i)$) can be evaluated. The generic element of such a matrix will be

$$B_{ij} = \langle F'(z_i)F'(z_j)\rangle \quad (2)$$

The eigenvectors $[u_k]$ (of elements $u_k(z_i)$) of the covariance matrix, which are the solutions of the eigenvalue problem

$$[B][u] = \lambda[u], \quad (3)$$

represent the sought natural orthogonal functions. Their ensemble is a complete set of orthogonal functions, and the profiles of deviations can be expanded in terms of the functions of this set:

$$F'(z_i) = \sum_{k=1}^{N} c_k u_k(z_i) \quad (4)$$

where the coefficients of the expansion are given by

$$c_k = [u_k]^T[F'] \quad (5)$$

This expansion has two important properties. The first one is that the NOF minimize the mean square error of the approximation (among all the possible choices of basis functions, for a fixed value of terms of the expansion) [*Obukhov*, 1960]. Second, only a few natural functions are required if we are not interested in the small-scale variations of the profile, which implies that only a

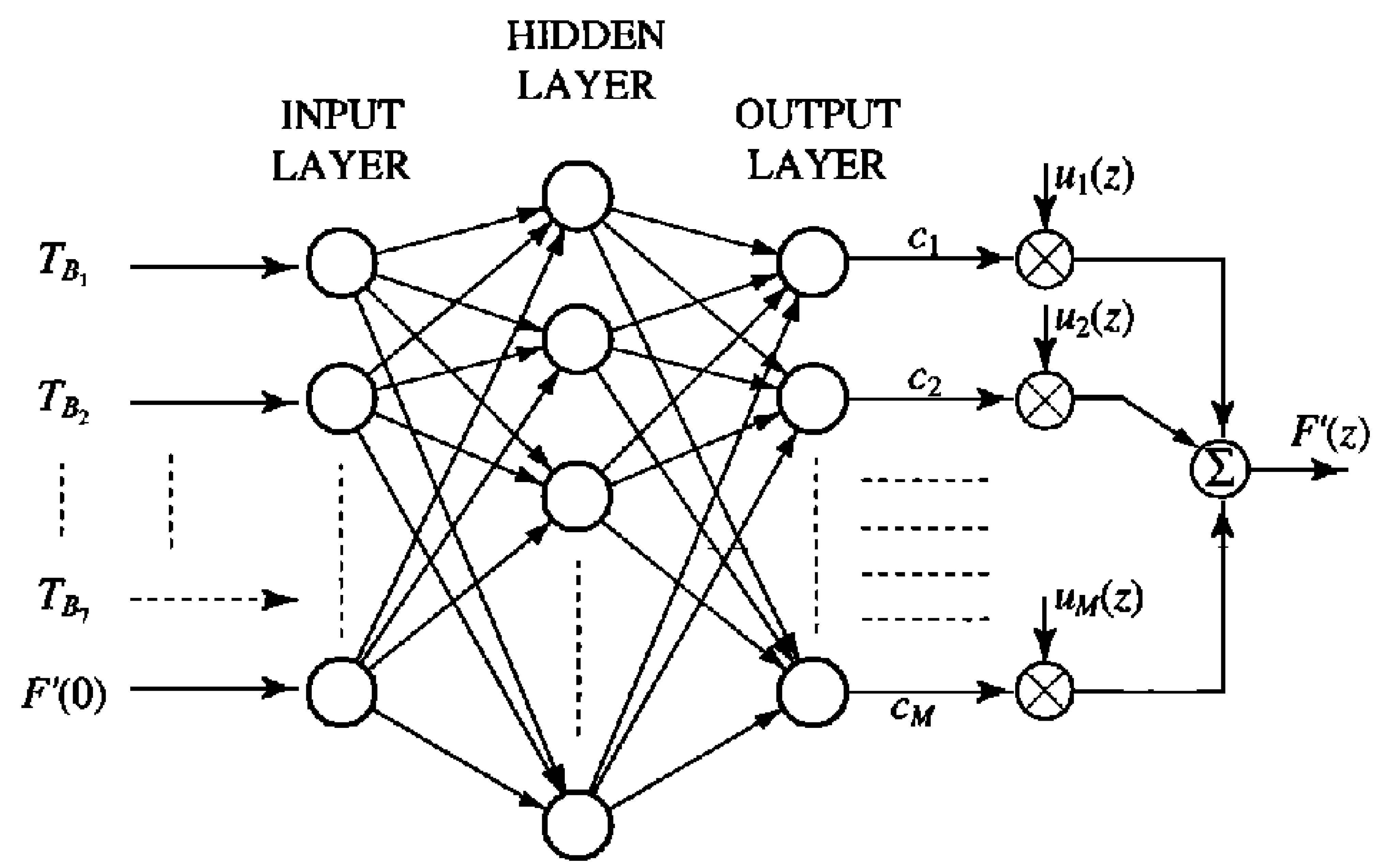

Figure 1. Block diagram of the natural orthogonal functions/neural network (NOF-NN) algorithm.

few coefficients have to be determined. Indeed, radiometers are generally more sensitive to the large-scale variations of the profiles rather then to their small-scale structure, which, in practice, is undetectable. The ensemble represented by the NOF is then particularly suitable if we want to expand the profiles to be retrieved in terms of functions that take into account the different orders of spatial fluctuations shaping up the profiles. Then, we can consider the following approximation for $F(z_i)$:

$$F(z_i) \approx \langle F(z_i) \rangle + \sum_{k=1}^{M} c_k u_k(z_i) \qquad (6)$$

with $M < N$. The problem of the computation of the coefficients c_k appearing in (6) is faced in the NOF-NN algorithm with a neural network which estimates the coefficients directly from the brightness temperatures and the ground measurements, as illustrated in Figure 1.

The topology of the net that we used was a standard feed forward perceptron with one hidden layer [*Rumelhart et al.*, 1986]. The activation function of each node of the perceptron has been the logistic function, which is defined as follows:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (7)$$

The software simulation of the net was performed by means of the Stuttgart neural network simulator (SNNS), developed at the University of Stuttgart (Germany) [*Zell et al.*, 1995], which proved to be a high-level, flexible, and reliable software package. The net has been trained using the back-propagation algorithm which easily runs on a medium speed CPU (the complete training process never took more than a few hours).

For determining when the training phase had to be stopped, we considered the early stopping procedure, which allows one to optimize the generalization properties of the net, avoiding an overtraining effect. This is achieved by constantly evaluating the performances of the net during the learning process, either on the training set or on a different independent validation set. In the training set the overall error in the retrieval of the correct output keeps on decreasing with the training until it reaches a value of convergence. Conversely, the error on the validation set will see a minimum value, after which it will start increasing if the process is continued. This is the point when the learning phase must be interrupted.

4. Results

The training set of profiles described in section 2 has been used to evaluate the NOF (equations (2) and (3)) and the coefficients of the corresponding expansion through (5). These coefficients constituted the output layer in the training phase of the neural network, while the inputs were the seven brightness temperatures and the ground measurement of the variable to be retrieved. The algorithm has then been tested on the evaluation set. The expansion has been limited to six terms. The retrieval of the coefficients for more terms did not significantly improve the performances, due to noise contribution and the already mentioned poor sensitivity of the radiometers to the small-scale variations of profiles. To make a comparison, a linear statistical inversion of the kind described by *Westwater* [1972] and *Hogg et al.* [1983] has been trained

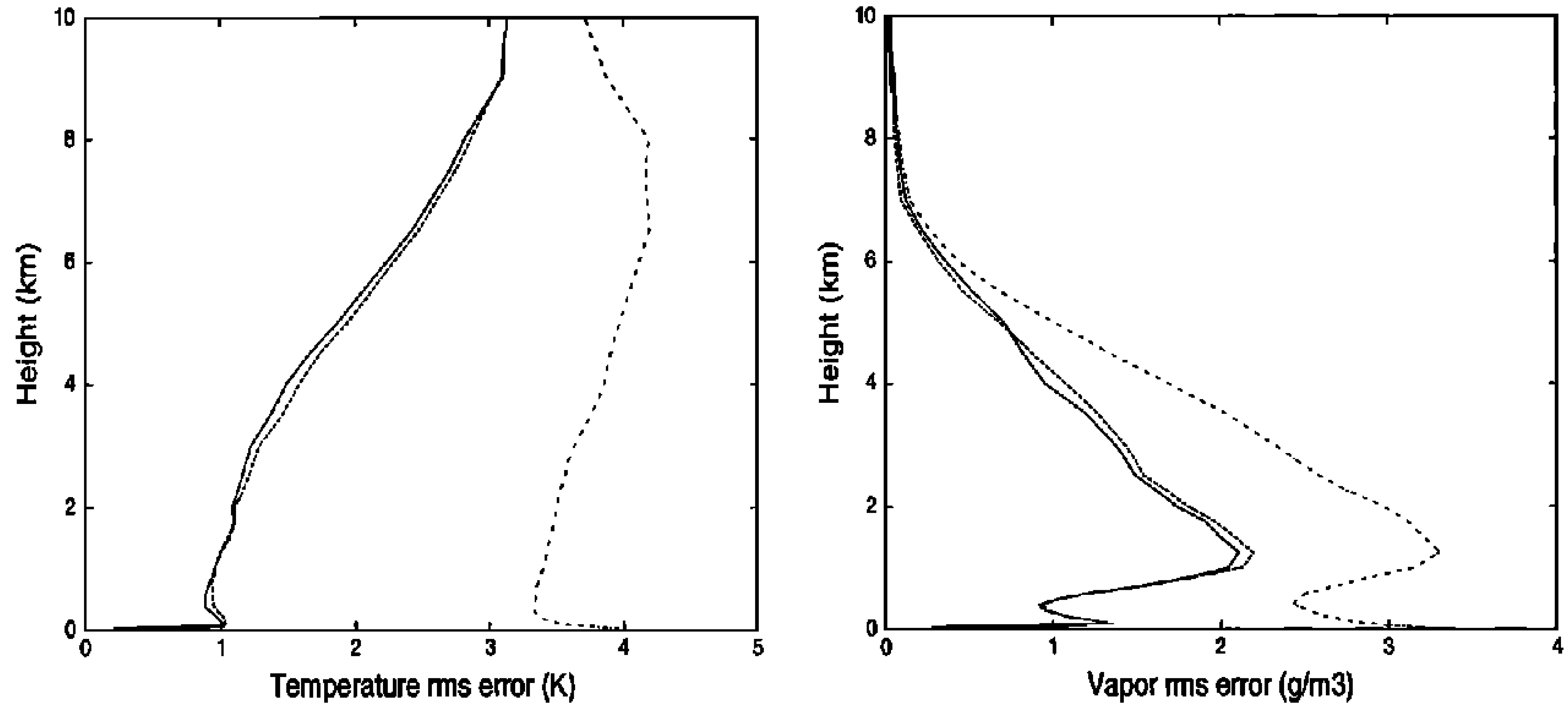

Figure 2. Profiles of rms error of retrieved temperature (left) and vapor (right). Solid line denotes the NOF-NN algorithm; dashed line denotes linear regression; and dash-dotted line denotes standard deviation of profiles from their means. Simulated input data are seven brightness temperatures.

and tested on the same data sets. With the same notations as in (1) and in Figure 1, the profiles of temperature and vapor are estimated by

$$F(z_i) = a_0(z_i) + \sum_{n=1}^{7} a_n(z_i) T_{B_n} + a_8(z_i)F(0) \qquad i = 1, 2, \ldots, N \qquad (8)$$

Note that the profile of coefficients $a_0(z_i)$ contains the mean climatological profile, and therefore the performances of the two methods are directly comparable. The profiles of rms error of the estimate with the NOF-NN technique and of the linear statistical inversion are reported in Figure 2. The standard deviation curve gives the a priori profiling accuracy without measurements. The accuracies of the two techniques are comparable, with slightly better performances of NOF-NN.

Of particular interest is the case of the inclusion of the height of the base of the cloud, provided by the ceilometer, in the input vector. This seems to strongly and pos-

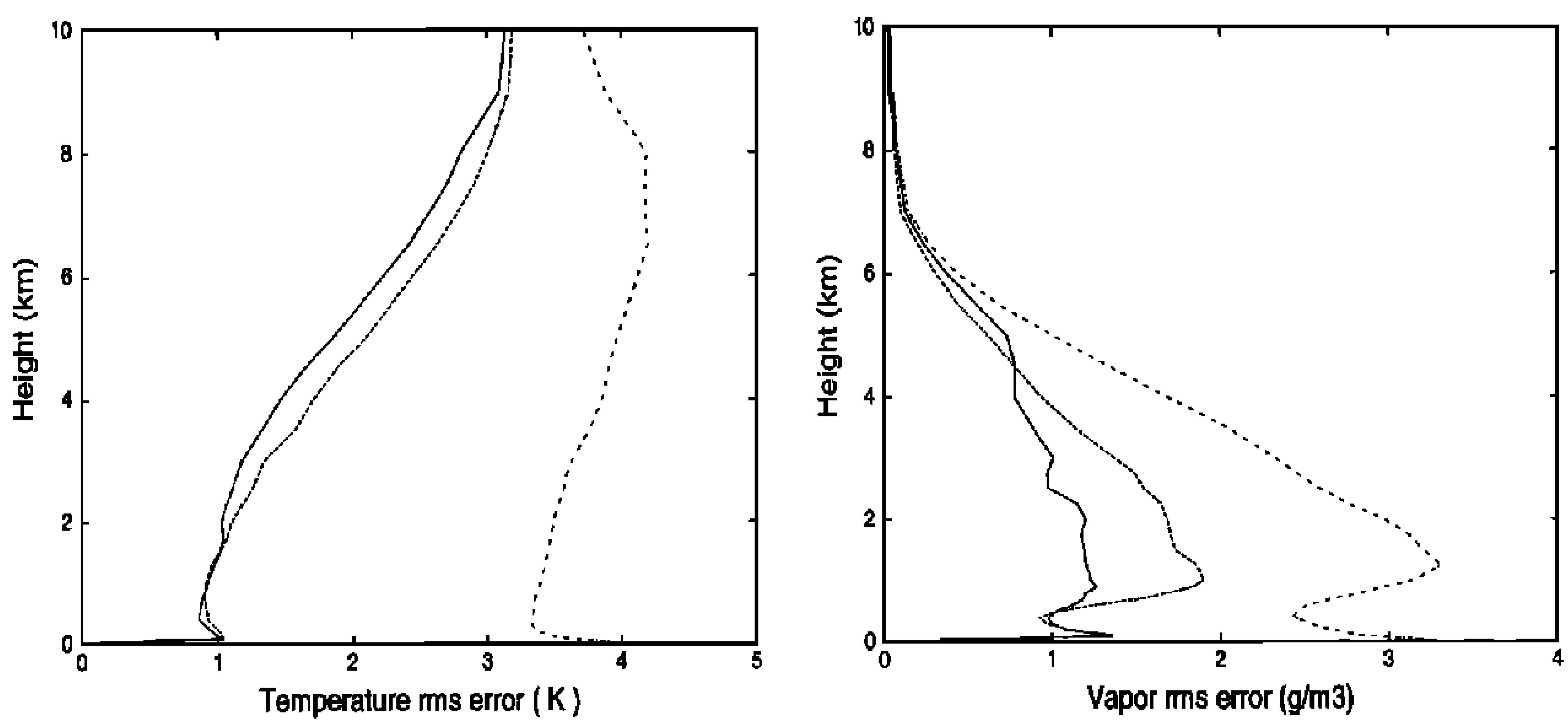

Figure 3. Profiles of rms error of retrieved temperature (left) and vapor (right). Solid line denotes the NOF-NN algorithm; dashed line denotes linear regression; and dash-dotted line denotes standard deviation of profiles from their means. Simulated input data are seven brightness temperatures and height of base of cloud.

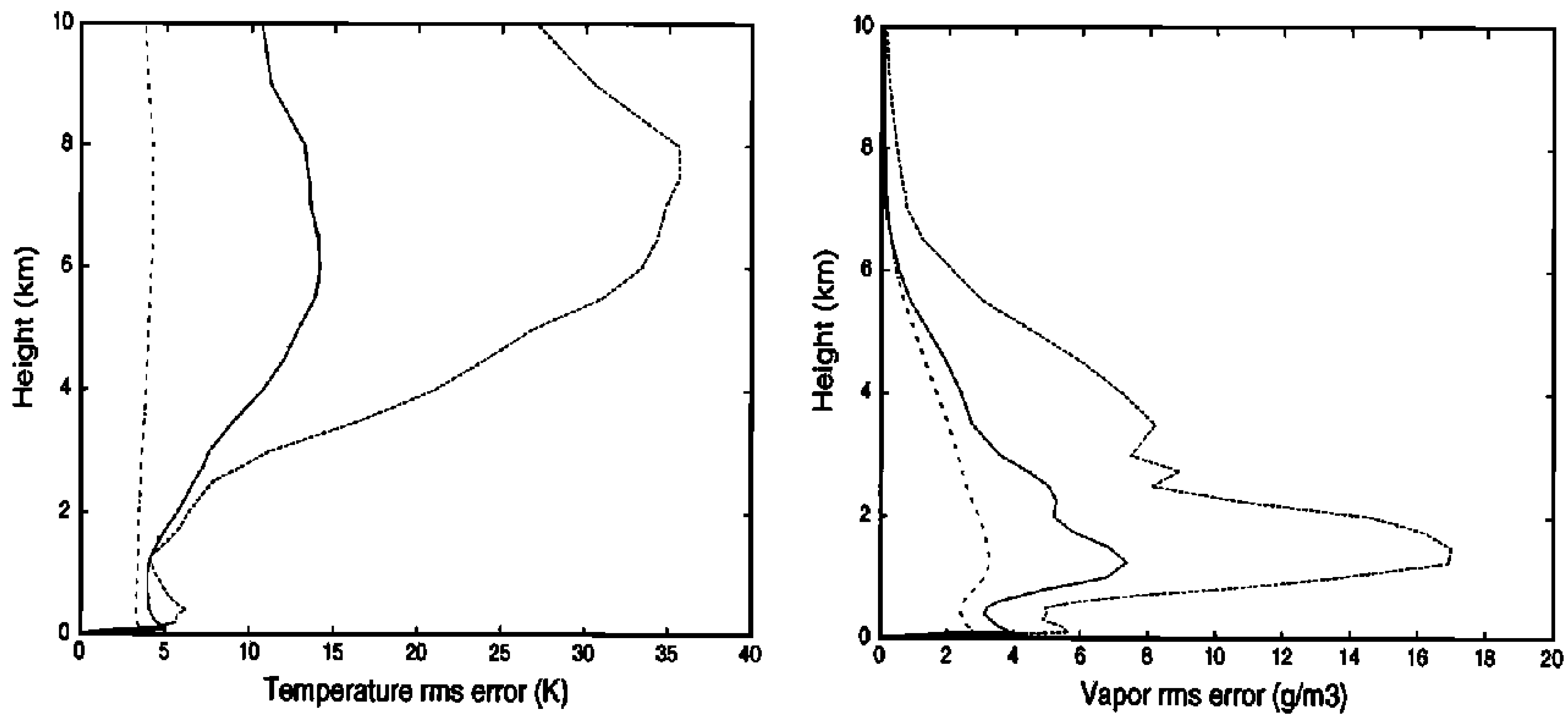

Figure 4. Profiles of rms error of retrieved temperature (left) and vapor (right) averaged over 14 cases of fault simulation. Solid line denotes the NOF-NN algorithm; dashed line denotes linear regression; and dash-dotted line denotes standard deviation of profiles from their means. Simulated input data are seven brightness temperatures.

itively affect the neural estimation procedure (Figure 3), especially for water vapor, for which, for the lower part of the profile, the performance improvement exceeds 30%. The same does not occur using the linear statistical inversion, which is not able to take advantage of the information provided by the ceilometer as the NOF-NN does. NOF-NN shows good properties of flexibility and portability, being able to effectively manage the measurements provided by a combined instrumentation.

Finally, we analyzed the algorithm from the point of view of its fault tolerance. To this aim, we simulated a set of masked fault conditions which would not be detected by a standard quality control procedure. In fact, some thresholds can be set to define acceptable physical ranges for the brightness temperatures measured by each channel of the radiometer. The detection of values outside these ranges can activate a recovery procedure which, for instance, makes use of an alternative algorithm for fewer channels, perhaps offline, or discards corrupted data. However, if the fault is such that the outputted data are within the set ranges, it would not be detected. One at a time, the brightness temperature of all seven channels was then permanently set to a value within an acceptable physical range but very close to either its upper or its lower bound, thus simulating a saturation problem. In Figure 4 we plot the overall averaged rms error profile resulting from all 14 cases. It can be noted that even though for the simulated worst cases the performances of the algorithm are considerably degraded, they neverthless remain better by far than those of the linear statistical inversion method.

5. Summary and Conclusions

We have presented the combined NOF-NN technique to retrieve the vertical distribution of atmospheric temperature and vapor. The profiles are expanded on a base of natural orthogonal functions, and the coefficients of the expansion are estimated by a neural network.

The performances of the algorithm are rather satisfactory. The reliability of the described procedure has been analyzed through some attributes including accuracy, flexibility, and robustness. Each of these aspects has been evaluated by a comparison with the results obtained using a linear regression technique.

The NOF-NN technique has been shown to provide an accuracy comparable to that of the linear statistical inversion, while it is more flexible, allowing an easy inclusion of measurements performed by mixed instrumentation. The robustness of the algorithm has also been tested by simulating an undetected failure of each channel of the radiometer. NOF-NN performs much better than linear statistical inversion in this case.

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