L. Tsang, Z. Chen, S. Oh, R.J. Marks II & A.T.C. Chang,
"Inversion of snow parameters from passive microwave remote sensing measurements by a neural network trained with a multiple scattering model",
Proceedings of the 1991 International Geoscience & Remote Sensing Symposium, 3-7 June 1991, Espoo, Finland.

# INVERSION OF SNOW PARAMETERS FROM PASSIVE MICROWAVE REMOTE SENSING MEASUREMENTS BY A NEURAL NETWORK TRAINED WITH A MULTIPLE SCATTERING MODEL

Leung Tsang, Zhengxiao Chen, Seho Oh, and Robert J. Marks II
Department of Electrical Engineering, University of Washington
Seattle, Washington 98195, U.S.A

A.T.C. Chang
Laboratory for Atmospheric Sciences (GLAS), Goddard Space Flight Center
National Aeronautics and Space Administration, Greenbelt, Maryland 20771, U.S.A

## ABSTRACT

The inversion of snow parameters from passive microwave remote sensing measurements are performed with a neural network trained with a dense media multiple scattering model. In this paper, we have performed the inversion of three parameters: mean-grain size of ice particles in snow, snow density, and snow temperature from five brightness temperatures. The five are 19 GHz vertical polarization, 19 GHz horizontal polarization, 22 GHz vertical polarization, 37 GHz vertical polarization, 37 GHz horizontal polarization which are available from SSMI satellites. The absolute percentage errors for mean-grain size of ice particles and snow density are less than 10%, and the absolute error for snow temperature is less than $3^0$ K.

Various techniques for solving inverse problems in remote sensing have been proposed in the last few decades [1-4]. In this paper, we use the artificial neural network technique to invert snow parameters from passive microwave remote sensing measurements. The basic idea is to use the input-output pairs generated by the scattering model to train the neural network [5]. Once the neural network is trained, it can invert parameters speedily from the brightness temperatures.

An artificial neural network can be defined as a highly connected array of elementary processors called neurons. In this paper we consider the multi-layer perceptron (MLP) type artificial neural network [6-10]. The MLP type neural network consists of one input layer, one or more hidden layers, and one output layer. Each layer employs several neurons and each neuron in the same layer is connected to the neurons in the adjacent layer with different weights. Signals pass from the input layer, through the hidden layers, to the output layer. Except for the input layer, each neuron receives a signal which is a linearly weighted sum of all the outputs from the neurons of the former layer. The neuron then produces its output signal by passing the summed signal through the sigmoid function $1/(1+e^{-x})$.

The backpropagation learning algorithm is used for training the neural network. Basically this algorithm uses the gradient descent algorithm to get the best estimates of the interconnected weights, and the weights are adjusted after every iteration. The iteration process stops when a minimum of the difference between the desired and the actual output is rearched by the gradient descent algorithm [9,10].

The scattering model that is used to train the neural network is the dense media radiative transfer theory [2-3]. In a dense medium with an appreciable fractional volume of scatterers (e.g. ice grains in snow), the assumption of independent scatterers that is used in conventional radiative transfer theory is not valid. This has been verified by controlled laboratory experiments and has been studied theoretically [11,12,13]. Recently, we have developed the dense medium radiative transfer theory which accounts for correlated scattering and which is derived from field theory using the quasicrystalline approximation of the Bethe-Salpeter equation [11,12,13]. The dense media theory also includes multiple scattering effects. The relations between the brightness temperatures and the snow parameters are nonlinear under the dense media multiple scattering model.

We first use the dense media theory to compute the brightness temperatures for a half-space snow medium for the five channels using different combinations of input parameters of mean-grain size of ice particles in snow $\langle a \rangle$, snow density $d$, and snow temperature $T$. A Rayleigh size distribution is assumed [14]. About 1000 sets of input-output pairs are generated in this manner which are well distributed in $\langle a \rangle$, $d$ and $T$. These are used as training data for the neural network. Using the error backpropagation algorithm on these sets results in a set of weighting coefficients. We note that the multi-frequency and two-polarization measurements are very important for the convergence of the weighting coefficients. Without either of them, the weighting coefficients diverge. The neural network then is tested by a set of synthetic testing data which are also generated by the passive dense medium theory and are randomly distributed in $\langle a \rangle$, $d$ and $T$. Figure 1 shows the absolute percentage error for $\langle a \rangle$ (the unit for $\langle a \rangle$ is in centimeters). Figure 2 shows the absolute percentage error for $d$ (the unit for $d$ is grams per cubic centimeter). Figure 3 shows the absolute error for $T$. (the unit for $T$ is in degrees Kelvin). Figures 1, 2, 3 demonstrate that increasing the number of iterations results in better convergence to the true value and hence lowers the errors. After 10,000 iterations, the absolute percentage error for $\langle a \rangle$ and $d$ are less than 10 %, and the absolute error for $T$ is less than $3^0$ K. We also note that the accuracy of the neural network inversion algorithm is dependent on the sensitivities of brightness temperatures to changes of medium parameters. If a change in $\langle a \rangle$, $d$ and $T$ results in large variations in the brightness temperatures of the five channels, then the neural network algorithm works well. Finally we also use the neural network with the trained weighting coefficients to invert the SSMI data over the Antarctica region [15]. The algorithm inverts 30,000 sets of 5-channel brightness temperatures of Antarctica in only 10 cpu minutes on a VAX 3500 workstation.

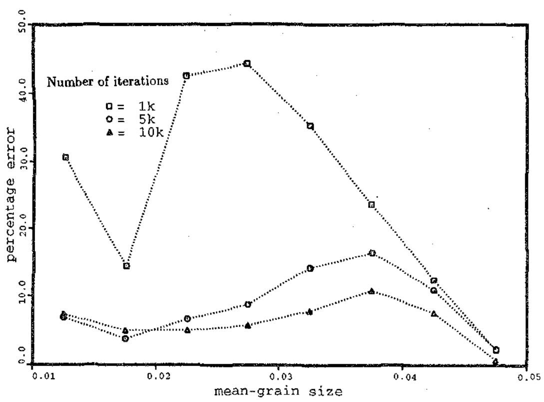


Figure 1

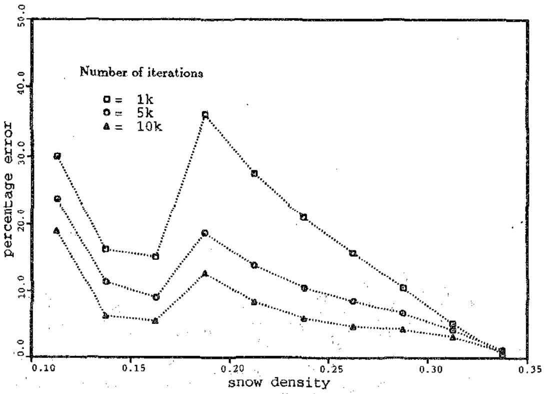


Figure 2

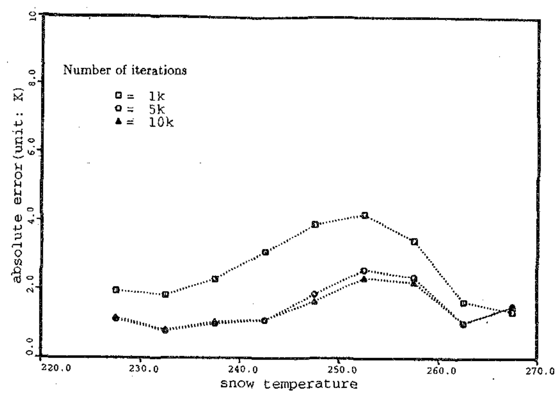


Figure 3

# REFERENCES

[1] D. L. Phillips, "A Technique for the Numerical Solution of Certain Integral Equations of the First Kind," J. Assoc. Comput. Mach. 9, pp. 84-97, 1962.

[2] P. Edenhofer, J. N. Franklin and C. H. Papas, "A New Inversion Method in Electromagnetic Wave Propagation," IEEE Trans. Antennas Propagat. AP-21, pp. 260-263, 1973.

[3] G. Backus and F. Gilbert, "Uniqueness in the Inversion of Inaccurate Gross Earth Data," Phil. Trans. R. Soc. London Ser. A266, pp. 123-192, 1970.

[4] E. R. Westwater and A. Cohen, "Application of Backus-Gilbert Inversion Technique in Determination of Aerosol Size Distributions from Optical Scattering Measurements," Appl. Opt. 12, pp. 1340-1348, 1973.

[5] A. Ishimaru, R. J. Marks II, Tsang L, C. M. Lam, and D. C. Park, "Particle Size Distribution Determination Using Optical Sensing and Neural Networks," Opt. Lett., vol. 15, no. 21, pp. 1221-1223, 1990.

[6] M. El-Sharkawi, R. Marks II, M. E. Aggoune, D. C. Park, M. J. Damborg and L. Atlas, "Dynamic Security Assessment of Power Systems Using Back Error Propagation Artificial Neural Networks," Proceedings of the 2nd Annual Symposium on Expert System Application to Power Systems, Seattle, WA, pp. 366-370, July, 1987.

[7] L. Atlas, R. Cole, Y. Muthusamy, A. Lippman, G. Connor, D. Park, M. El-Sharkawi and R. Marks II, "A Performance Comparison of Trained Multi-layer Perceptrons and Trained Classification Trees," submitted to Proceedings of IEEE Special Issue on Neural Networks, August 1990.

[8] D. Park, M. El-Sharkawi, R. Marks II, L. Atlas and M. Damborg, "Electrical Load Forecasting Using an Artificial Neural Network," submitted to IEEE Power Engineering Society Winter Meeting, 1990.

[9] D. E. Rumelhart and J. L. McClelland (Eds.), *Parallel Distributed Processing*, Cambridge, MA, MIT Press, 1986.

[10] R. P. Lippmann, "Introduction to Computing with

Neural Nets," IEEE Trans. Acoust. Speech Signal Process. pp. 4-22, April 1987.

[11] L. Tsang, J. A. Kong, and R. T. Shin, *Theory of Microwave Remote Sensing*, Wiley-Interscience, New York, 1985.

[12] B. Wen, L. Tsang, D. P. Winebrenner, and A. Ishimaru, "Dense Medium Radiative Transfer Theory: Comparison With Experiment and Application to Microwave Remote Sensing and Polarimetry," IEEE Trans. Geosci. Remote Sensing, vol. 28, pp. 46-59, 1990.

[13] L. Tsang, "Passive Remote Sensing of Dense Nontenuous Media," J. Electromagnetic Waves and Applications, vol. 1, no. 2, pp. 159-173, 1987.

[14] R. D. West, *Polarimetric Radar Signatures for Two Layers of Dense Random Media*, M. S. Thesis, University of Washington, 1990.

[15] A. T. C. Chang, B. J. Choudhury, and P. Gloersen, "Microwave Brightness of Polar Firn as Measured by Nimbus 5 and 6 ESMR," J. Glaciology, vol 25, no. 91, 1980.