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A Neural Network Approach to Inversion of Snow Water Equivalent from Passive Microwave Measurements

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The inversion of snow water equivalent, SWE, from passive microwave remote sensing measurements may be accomplished by using a neural network trained with a dense media multiple scattering model. Brightness temperatures from 19 GHz vertical and horizontal polarizations, 22 GHz vertical polarization and 37 GHz vertical and horizontal polarizations which are available from the SSM/I sensors, are used as input to the neural network. The percentage error for estimated SWE varies from 9% to 57% for different snow conditions.

Introduction

Various techniques for solving inverse problems in remote sensing have been used in the last few decades (Phillips 1962; Edenhofer *et al.* 1973; Backus and Gilbert 1970). However, in retrieving snow parameters from microwave measurements, these techniques are usually not robust enough to give consistent results from very different snow conditions. Multiple linear regressions, theoretically derived and empirically derived formulae have been used in many cases for snow parameter retrieval (Rott and Ashbarcher 1989; Chang *et al.* 1991; Chang *et al.* 1976). Recently, Lure *et al.* (1992) used a neural network approach to classify snow cover with some success.

Neural networks have been considered as having potential for improving retrieval accuracy in geophysical data. It appears that neural networks could perform as well as or better than other techniques, and they require no assumptions about the parametric nature of distributions of the data to be classified (*e.g.* normal distribution). Neural networks, once trained, are very efficient in performing computations. Comparisons of the results from neural network and from multiple regression method indicate that neural networks can achieve a parity of performance if the training data set is sufficiently large enough.

In a previous paper (Tsang *et al.* 1991) neural network approach has been used to retrieve snow parameters in a half space model. In this paper we use the technique to retrieve SWE and other parameters from a model of a snow layer of finite thickness. Input (microwave brightness temperatures) and output (SWE) pairs generated by the scattering model will be used to train the neural network. Simulated data will be used for training and testing the neural network. Once the neural network is trained; it can rapidly retrieve the parameters from the brightness temperature.

Background

a) Neural Network

An artifical neural network can be defined as a highly connected array of elementary processors called neurons. The neural network approach is attractive because it has the capability to learn patterns whose complexity makes them difficult to define using formal approaches. Also, neural networks have the ability to integrate information from multiple sources and to incorporate new features without degrading prior learning. In this paper, we consider the multi-layer perceptron, MLP, type artifical neural network (El-Sharkawi *et al.* 1987; Rumelhart and McClelland 1986; Lippmann 1987).

As shown in Fig. 1, 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.

The activity at an input neuron represents the value of some input signal. If the activity of neuron K is denoted by V_k and a weight on a path from neuron L to neuron K is denoted by W_{KL}, then a simple model for the activity at neuron K is given by

$$V_K = f(W_{KL}\, V_K - H) \qquad (1)$$

where f is an appropriately chosen nonlinear function and H is a threshold.

For the output neuron, a neural network may be viewed as a nonlinear vector-valued function relating to the input neurons. From this simple viewpoint, neural networks are mechanisms for performing computations. Signals pass from the

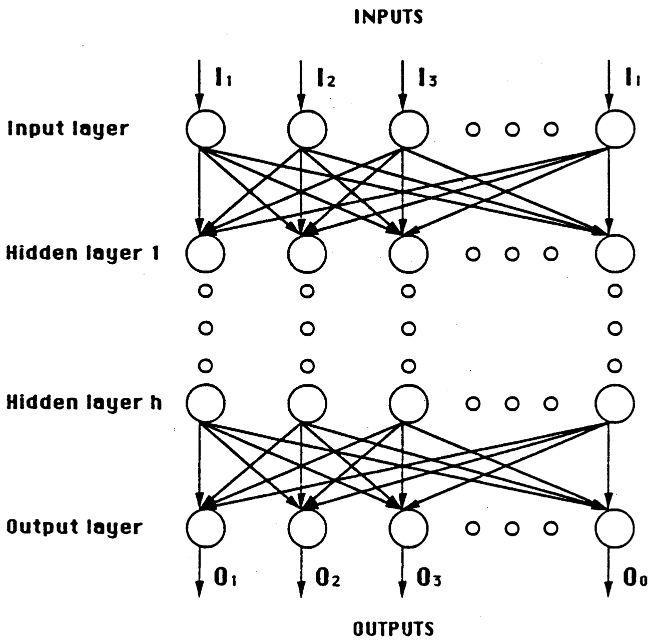

Fig. 1. Structure of a multi-layered perceptron type artifical neural network.

input layer, through the hidden layers to the output layer. Except for neurons of the input layer, each neuron receives a signal which is a linearly weighted sum of all the outputs from the neurons of the formal 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 employed for training the neural network. Basically this algorithm uses the gradient descent algorithm to get the best estimates of the interconnected weights, and to make the output of the network as close to the desired values as possible for the given input training sets. The iteration process stops when a minimum of the difference between the desired and actual output is reached. More detailed descriptions of the backpropagation algorithm can be found in other references (Rumelhart and McClelland 1986; Lippmann 1987). The procedures that we describe and use here is the techniques of explicit inversion in neural network. There are other techniques such as the constrained iterative inversions (Chen *et al.* 1992) which can perform better for some cases.

b) Microwave Scattering of Snow

Microwave emission from a layer of snow over ground consists of two major parts: 1) emission by the snow volume and 2) emission by the underlying ground. Both

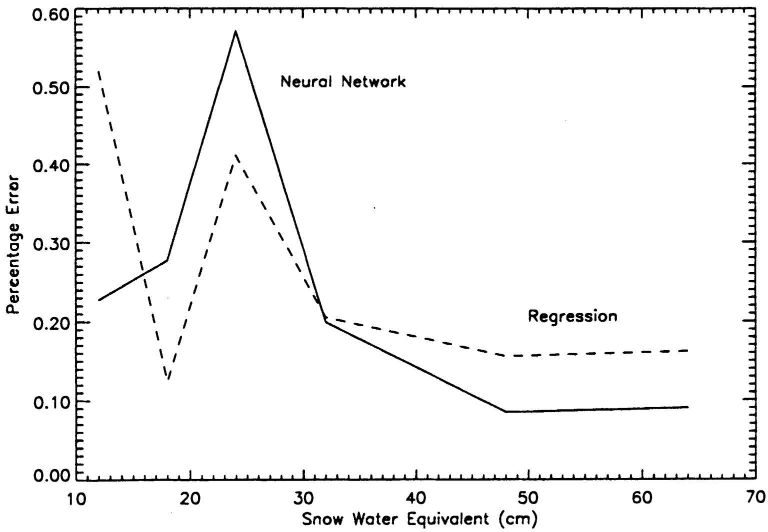

Fig. 2. Calculated microwave brightness temperatures for 37 and 19 GHz Vertical polarization for different mean snow radii and snow water equivalents.

contributions are governed by the transmission and the reflection properties of the air-snow and snow-ground interfaces and by the absorption and scattering properties of the snow layer. Dry snow is a low loss dielectric medium, absorption by the snow crystals is not significant. The effect of scattering is determined by the size, distribution and thickness of the snowpack. When the snow crystal sizes are comparable to the wavelength, scattering becomes the dominate factor for the upwelling radiation. Mie scattering theory is used to account for the energy redistribution by the snow crystals. Although the snow crystal usually is not spherical in shape, its ensemble scattering properties can be mimicked by spheres (Chang *et al.* 1976).

In a dense medium with an appreciable fractional volume of scatterers, the assumption of independent scatterers that is used in conventional radiative transfer theory is not valid. This has been verified by controlled laboratory experiments (Ishimaru and Fuga 1982) and has been studied theoretically (Tsang *et al.* 1987; Wen *et al.* 1990). Recently a dense medium radiative transfer theory which accounts for correlated scattering has been developed (Tsang 1987). Based on the field theory and using the quasi-crystalline approximation of the Bethe-Salpeter equation, emerging microwave radiation from a snowpack can be calculated. Fig. 2 shows calculated brightness temperatures as a function of mean grain size for 19 and 37 GHz vertical polarization.

The Special Sensor Microwave Imager (SSM/I) is a four frequency (19.35, 22.235, 37 and 85.5 GHz) microwave radiometer on the near-polar, sun synchronous Denfense Meteorological Satellite Program (DMSP) satellite. The spatial resolution varies from 69 × 43 km at 19.35 GHz to 15 × 13 km at 85.5 GHZ. The antenna scans by continuous rotation with a period of 1.9 seconds along a conical surface with a vertical axis and a half angle of 45°, which intersects the earth's surface at an angle of 53° (incidence angle). The scan swath width is 1,400 km from the 833 km satellite altitude. It measures the radiation in both horizontal and vertical polarizations at all frequencies except 22.235 GHz where it only measures the vertically polarized component. The SSM/I data can be used to derive snow parameters. However, coincident snow water equivalent data and microwave data for large areas are difficult to obtain. Also, due to the strong atmospheric effect on the 85 GHz data, we will not use these data for snow retrieval.

Neural Network Training

Microwave brightness temperature for a snowpack with varying depths for the five lower frequencies of the SSM/I sensor are calculated. Different combinations of three input parameters are used: the mean grain size of ice crystals in the snowpack $<a>$ assuming a Rayleigh size distribution, snow density d, and snow depth T. The snow temperature is assumed to be constant at 265 K. In addition, a model atmosphere is then superimposed onto the calculated emerging microwave radiations from snow surface. Mid-latitude winter, sub-Arctic winter and Arctic winter atmospheres are used in the calculations. A total of 720 sets of input output pairs are generated in this manner which are well distributed in $<a>$, d and T. These data are used as the training data for the neural network. In the inversion, all these parameters $<a>$, d and T are inverted. Since hydrologists are more interested in total snow storage in a snowpack, the output parameter that we show for this study is the SWE, which is the product of density d and snow depth T. Using the error backpropagation algorithm on these data results in a set of weighting coefficients. After 10,000 iterations, the neural network was able to retrieve SWE estimates having errors of approximately 25%. Multifrequency and dual polarization measurements are very important for the convergence of the weighting coefficients. Without them the weighting coefficients diverge. Training processes were also performed using every other point (360 training sets) and every third point (240 training sets) of the simulated data set.

Results

Three trained neural networks are then tested by a set of simulated test data which are also generated by the dense medium theory. The standard error of estimates for the three trained neural networks are 8.4 cm, 19.9 cm and 27.9 cm respectively. By using a smaller training set the results from the neural network tends to deteriorate quickly, and the SWE is over estimated when the snowpack is shallow.

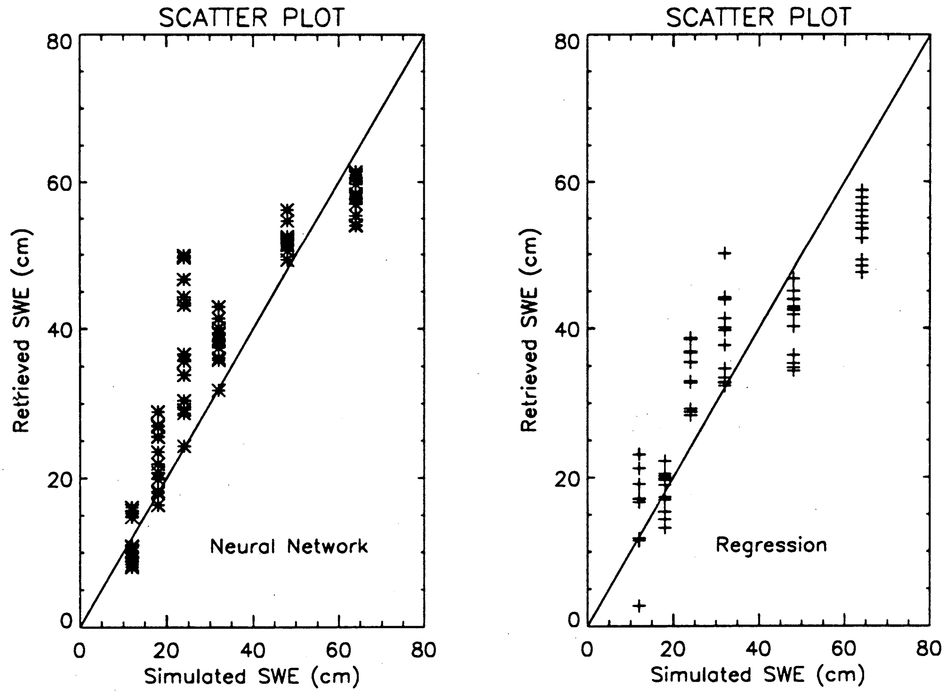

Fig. 3. Scatter plots for simulated SWE versus retrieved SWE by a) neural network and b) regression.

Multiple linear regression is commonly used in retrieving physical parameters from multichannel data. Five channels of brightness temperatures (19H, 19V, 22V, 37H, and 37V) are used for the regression analysis. By using the simulated data set, the regression can account for 72% of the variance. The mean and standard deviation of the simulated SWE set is 31.5 and 20 cm respectively. The standard error of estimate from regression analysis is 10.6 cm, thus reducing the error by approximately 50%. The standard error of estimate when applying the regression relation to the test data set is 8.7 cm. Fig. 3 shows the scatter plots for estimated SWE versus simulated SWE using both methods. The results of these two methods are quite comparable. However, by reducing the regression data set to one half, one third or even one fourth of the original sample size, does not vary the correlations and standard error of estimates greatly. This probably is due to the fact that the distribution of the sample data set is very uniform. Therefore, reducing the size of the regression data set do not change the final results.

The standard error of estimates using the neural network (8.4 cm) is slightly better than the regression method (8.7 cm) when the 720 pairs of simulated data were used. By reducing the sample number, the performance of the regression method did not vary much, whether the data set consists of 720, 360 or 240 samp-

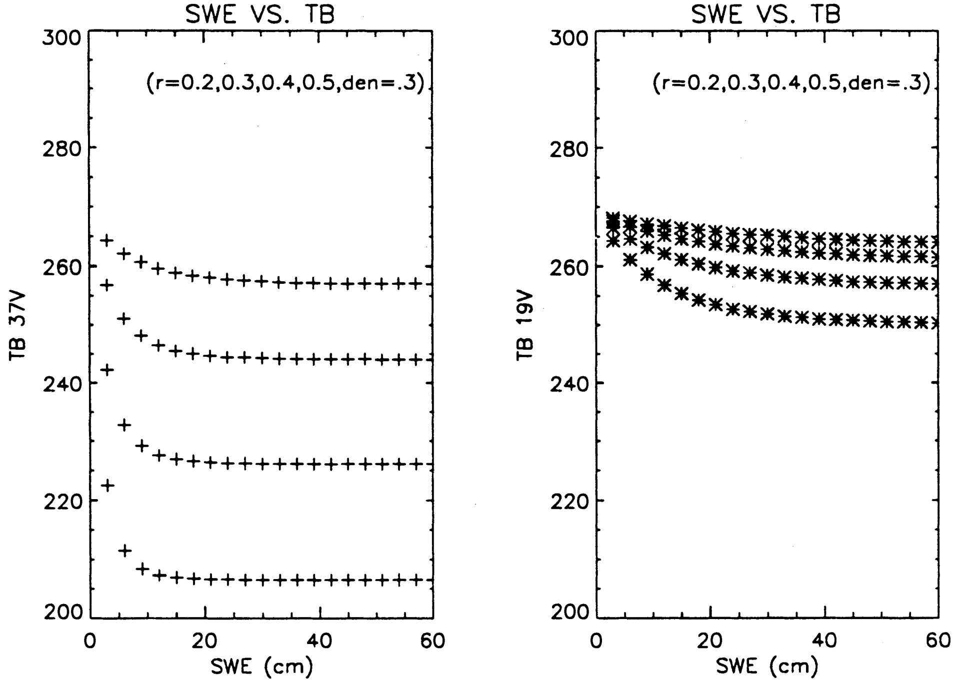

Fig. 4. Percentage error of retrieved SWE by neural network method and regression method.

les. However, the standard error of estimates for three neural networks varied from 8.4 cm to 19.9 cm and 27.9 cm when networks were trained with smaller data sets. Fig. 4 demonstrates that percentage errors for both methods of the estimated SWE is not uniform with respect to snow depth range. Neural networks do better for SWE estimates in the low (12 cm) and high SWE range (greater than 32 cm), while regression method seems to do better in the mid range (18 to 24 cm). This is consistent with the fact that the regression method generally performs well around the sample average.

Conclusions

In this study backpropagation multiple layered neural networks were used to estimate the SWE of a snowpack using simulated data and the technique of explicit inversion. When using the entire simulated data set (720 cases), results from using neural networks seem to reproduce the simulated data set better than when using the multiple regression method. By reducing the size of the training set, the accuracy of the SWE retrievals using the neural networks decreased rapidly, However, reducing the size of training data set does not affect the results of the regression method. More studies will be performed to extend this comparison using actual snow data over large areas with different snow conditions and physiographic regions.

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References

Backus, G., and Gilbert, F. (1970) Uniqueness in the inversion of inaccurate gross Earth data, Phil. Trans. Roy. Soc. London Ser. A266, pp. 123-192.

Chang, A. T. C., Foster, J. L., Rango, A., and Josberger, E. G. (1991) The use of microwave radiometry for characterizing snow storage in large river basin, Proceedings of the IAHS Remote Sensing Symposium, Vienna, pp. 73-80.

Chang, T. C., Gloersen, P., Schmugge, T., Wilheit, T. T., and Zwally, H. J. (1976) Microwave emission from snow and glacier ice, *J. Glaciology, Vol. 16.* pp. 23-29.

Chen, Z., Davis, D. T., Tsang, L., Hwang, J. N., and Chang, A. (1992) Inversion of snow parameters by a neural network with iterative inversion. Submitted to IEEE International Geoscience and Remote Sensing Symposium, Houston, Texas, May 1992.

Edenhofer, P., Franklin, J. N., and Papas, C. H. (1973) A new inversion method in electromagnetic wave propagation, IEEE Trans. Antennas propagation, AP-21, pp. 260-263.

El-Sharkawi, M., Marks II, R., Aggoune, M. E., Park, D. C., Damborg, M. J., and Atlas, L. (1987) Dynamic security assessment of poder 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.

Ishimaru, A., and Fuga, Y. (1982) Attenuation constant of a coherent field in a dense distribution of particles, *J. Optical Society of America, Vol. 72,* pp. 1317-1320.

Lippmann, R. P. (1987) Introduction to computing with neural nets, IEEE Trans. Acoustic Speech Signal Processing, pp. 4-22.

Lure, Y. M. F., Glody, N. C., Yeh, H. Y. M., and Lin, J. S. J. (1992) Neural network approaches to classification of snow cover and precipitation from spectral sensor microwave imager (SSM/I), Proceedings of the Eighth International Conference on Interactive Information and Processing Systems (IIPS) for Meteorology, Oceanography and Hydrology, Atlanta, GA, January 5-10, 1992.

Phillips, D. L. (1962) A technique for the numerical solution of certain integral equations of the first kind, *J. Assoc. Comput. Mach., Vol. 9,* pp. 84-97.

Rott, H., and Aschbacher, J. (1989) On the use of satellite microwave radiometers for large-scale hydrology, Proceedings of IAHS 3rd Int. Assembly on Remote Sensing and Large Scale Global processes, Baltimore.

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

Tsang, L. (1987) Passive remote sensing of dense non-tenuous media, *J. Electromagnetic Waves and Applications, Vol. 1,* pp. 159-173.

Tsang, L., Kong, J. A., and Shin, R. T. (1987) *Theory of Microwave Remote Sensing,* Wiley-Interscience, New York.

Tsang, L., Chen, Z., Oh, S., Marks II, R., and Chang, A. (1991) Inversion of snow parameters from passive microwave remote sensing measurements by a neural network trained with a multiple scattering model. Proceedings of 1991 IEEE International Geoscience and Remote Sensing Symposium, 1965-1968, Espoo, Finland, June 3-6, 1991.

Wen, B., Tsang, L, Winebrenner, D. P., and Ishimaru, A. (1990) Dense medium radiative transfer theory: Comparison with experiment and application to microwave remote sensing and polarimetry, *IEEE Trans. Geoscience and Remote Sensing, Vol. 28,* pp. 46-59.

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