IDENTIFICATION OF MOUNTAIN SNOW COVER USING SSM/I AND ARTIFICIAL NEURAL NETWORK

Changyi Sun
Forest Resources, Utah State University, Logan, UT 84322-5215, USA

Heng-Da Cheng
Computer Science, Utah State University, Logan, UT 84322-4205, USA

Jeffery J. McDonnell
Environmental Science and Forestry, SUNNY, Syracuse, NY 13210-2779, USA

Christopher M.U. Neale
Biological and Irrigation Engineering, Utah State University, Logan, UT 84322-4105, USA

ABSTRACT

The Special Sensor Microwave/Imager (SSM/I) radiometer is practical in monitoring snow conditions for its sensitive response to the changes in snow properties. A single-hidden-layer artificial neural network (ANN) was employed to accomplish this remote sensing task, with radiometric observations of brightness temperatures (Tb's) as input data, to derive information about snow. Error back-propagation learning was applied to train the ANN. After learning the mapping of SSM/I Tb's to snow classes, ANN approach showed a significant promise for identifying mountainous snow conditions. Error rates were 3% for snow-free, 5% for dry snow, 9% for wet snow, and 0% for refrozen snow, respectively. This study indicates the potential of ANN supervised learning for the inversion of snow conditions from SSM/I observations. Further improvement on the application of ANN for large-scale snow monitoring can be expected by using more training data derived from both plains and mountain regions.

1. INTRODUCTION

Snow cover is a main factor controlling the hydrological response of watersheds in mid and high latitudes by which it plays an important role in the global climate system. Snow on the ground can be classified as either dry or wet depending on whether it is below or at its melting temperature. In order to determine where snow exists and when snowmelt occurs, monitoring snow conditions throughout the snow season is essential in snow hydrology.

The Special Sensor Microwave Imager (SSM/I) is becoming an useful tool in monitoring snow conditions for its sensitive response to the changes of snow physical and dielectric properties. In a dry snow layer, the radiation emitted from background can be scattered on its way to the surface by ice crystals. When snow is wet, the liquid water held on the snow grains causes a significant increase in volume absorption by which more radiation is re-emitted. Thus, large-scale characterization of seasonal snowpack conditions is possible through utilization of SSM/I observations.

The SSM/I is a seven-channel, four-frequency, linearly polarized, passive microwave radiometric system. To date, three of the seven SSM/I radiometers have been launched on the Defense Meteorological Satellite Program (DMSP) F-8, F-10, and F-11 satellites. The spatial resolution or footprint of a SSM/I radiometer is defined as the area on the ground scanned by the antenna main-lobe. A SSM/I receives both vertically (V) and horizontally (H) linearly polarized radiations at 19-, 37-, and 85-GHz and vertical only at 22-GHz [1]. Hence, seven brightness temperatures (Tb's), T19V, T19H, T22V, T37V, T37H, T85V, and T85H, are observed at each footprint.

Based on statistical analysis of SSM/I data, Neale *et al.* [2] and McFarland and Neale [3] worked out a land-surface-type (LST) classification scheme by using Tb combination rules to identify dry, wet, and refrozen snow over land. Fiore Jr. and Grody [4] developed a decision-tree algorithm, using SSM/I Tb's at 19-, 37-, and 85-GHz, for the global classification of snow cover over large regions. However, these methods have limitations as general approaches for complex terrain such as forested or mountainous areas where microwave emission of SSM/I footprint is extremely complex and nonlinear involving many variables which are interconnected.

Recently, the use of artificial neural network (ANN) approach to retrieve snow parameters from passive microwave data has been well addressed [5], [6], [7]. Studies have shown that neural networks have the potential

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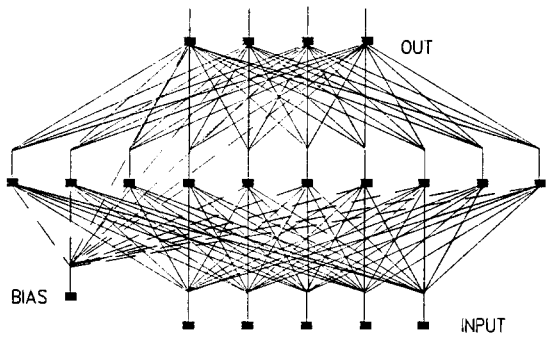

Layer	Function		Learning	
	Summation	Transfer	Rule	Rate
Out	Weighted Sum	TanH	Norm-Cum-Delta	0.15
Hidden	Weighted Sum	TanH	Norm-Cum-Delta	0.30
Input	None	Linear	None	None

Fig. 1. Structure of the single-hidden-layer artificial neural network and its settings.

to learn Tb patterns whose complexity and nonlinearity make retrieval accuracy of formal approaches uncertain.

Accordingly, the purpose of this study was to seek the solution to the improvement of SSM/I snow classification algorithm using neural network approach. In this work, error back-propagation learning method was applied to train a single-hidden-layer ANN. Training data set of input/output pairs were prepared by matching SSM/I data to the Soil Conservation Service (SCS) SNOTEL (SNOwpack TELemetry) ground truth. By learning the mapping of inputs (SSM/I Tb's) to outputs (snow conditions), it is concluded that the ANN is able to classify snow conditions with given input of SSM/I measurements.

2. METHODOLOGY

2.1. Design of ANN Structure

A neural network software by NeuralWare Inc. is used to develop a single-hidden-layer ANN which is suitable for training by the back-propagation algorithm. The ANN consists of one input layer, one hidden layer, and one output layer (Fig. 1). Each layer contains several neurons, and neurons of adjacent layers are fully connected with different weights.

In the input layer, the number of neurons is determined by SSM/I Tb's. Since the increase in noise level of both SSM/I 85-GHz channels on F-8 was observed in 1988, five neurons in the input layer are needed for the inputs of T19V, T19H, T22V, T37V, and T37H. For the hidden layer, however, 10 neurons are chosen by experiment. The four neurons in output layer are decided by the number of snow classes, which are snow-free, dry snow, wet snow, and refrozen snow. In addition, a bias neuron, used as the same idea as incorporation of the constant in a regression, is connected to hidden and output layers.

In the ANN, the connection weights between the layers are randomly initialized with a range around ±0.1 before training.

2.2. Collection of Input and Output Pairs

The ANN designed in this study requires training in a supervised learning mode. This mode of learning assumes that when the input is applied, the desired output is also provided. Thus, a set of SSM/I Tb's with corresponding ground snow classifications is required for the learning.

SSM/I and SNOTEL data, from Oct. 1, 1989 to Sep. 30, 1990, at mountainous areas in Utah were selected to generate the input and output patterns. DMSP-F8 SSM/I data, which contain the latitude/longitude (lat/lon) coordinates of each footprint and corresponding Tb's, were derived from the Naval Research Laboratory. SNOTEL data of snow water equivalent (SWE), precipitation, and air temperatures (i.e., maximum, mean, and minimum) were provided by the SCS West National Technical Center.

Based on SNOTEL data, daily snow condition at each station was classified as snow-free if SWE equaled to zero, dry snow while SWE accumulated, and wet snow as SWE decreased after the day of maximum SWE was passed. While snow was wet, if the mean temperature was below freezing point, the snow cover was classified as refrozen. Categories of different snow conditions were binary-coded as (1, 0, 0, 0) for snow-free, (0, 1, 0, 0) for dry snow, (0, 0, 1, 0) for wet snow, and (0, 0, 0, 1) for refrozen snow.

Both SSM/I and SNOTEL data files were merged by first locating the snow data of which the lat/lon coordinates were within a search radius of 15-kilometer of each SSM/I footprint lat/lon coordinates, and then placing the corresponding seven SSM/I Tb's along with matched binary-coded snow conditions to create the database of input and output pairs.

2.3. Selection of Training and Test Data Sets

In order to assure that the ANN was learned from the correct classification patterns, discriminant analysis was applied to examine the selected input and output pairs. With the four known categories of snow condition, each input of SSM/I Tb's was classified into one of the

Table 1. Elements selected for the ANN training and test.

Sow Condition	Number of Elements in Data Set		
	Training	Test	Total
Snow-free	200	76	276
Dry	200	163	363
Wet	200	49	249
Refrozen	200	102	302
Total	800	389	1190

categories. Mis-classified data of input and output pairs were eliminated from each group. Accordingly, a data set of prototype classification patterns was constructed for ANN learning.

Training and test data sets were completely separated from the prototype input and output patterns. The training data set was designed to maximize the learning process. Thus, the snow category with smaller size of pattern elements was enlarged to about the size of the largest, which was done by extrapolating certain inputs of SSM/I Tb's within the Tb range of that category.

Consequently, an equal amount of elements was randomly selected from each snow category to form the training data set. Test data set was created by selecting the remaining elements in each snow category. Table 1 shows the elements prepared for the ANN.

2.4. Error Back-propagation Training

The main mechanism in a error back-propagation training is first to allow inputs to flow forward through hidden layer to output layer [8]. Inputs of the five Tb's are scaled between -1 and 1. Scaled data are passed directly as mapping outputs through connection weights from the input layer to the hidden layer. However, each neuron in the hidden layer and output layer decides its output by calculating the net, which is the sum of all of its incoming connection weights (w_j) multiplied by the mapping outputs (m_j) from previous layer:

$$net^S = \sum_j m_j^{S-1} w_j$$

where S denotes the state of current layer. Then, the net is transferred by the hyperbolic tangent (TanH) function to give an mapping output between -1 and 1:

$$m^S = f(net^S) = (1 + f(net^S))(1 - f(net^S))$$

After calculating mapping outputs in the output layer, error between desired output (d) and mapping output (m) for a neuron is measured according to the delta learning rule:

$$E^S = \frac{1}{2}(d^S - m^S)^2 = \frac{1}{2}(d^S - f(net^S))^2$$

Measured error is then propagated backward from layer to layer to adjust connection weights using gradient descent optimization method:

$$\nabla E^S = -\partial E^S/\partial w_j = -(\partial E^S/\partial m^S)(\partial m^S/\partial w_j) = -(d^S - m^S)\, f'(net^S)\, m_j^{S-1}$$

which changes the weight in a direction that minimizes the error. Since there is no desired output for hidden layer, a weighted sum of error gradients is propagated back from output layer to each neuron in the hidden for error gradient computation. Then, the gradient component for a weight update is specified as:

$$\Delta w_j = -\eta \nabla E^S$$

where η is the learning rate, typically less than 1.0. According to the experience [8], having a larger learning rate at the hidden layer than that at the output layer can decrease learning time. Learning rates are set at 0.30 for hidden layer and 0.15 for output layer (Fig. 1). Once the gradient component is found, each connection weight to the output layer is updated by:

$$w_j^t = w_j^{t-1} + \Delta w_j$$

where t is the time when the weight is updated.

Training step, involving forward feeding neuron outputs through layers and backward propagating errors for weight adjustment, is repeated until a given threshold of root-mean-square (RMS) error set up at 0.01 is reached.

2.5. ANN Test

After learning, the test data set was applied to evaluate the ANN retrieval accuracy by calculating the error rate (%) in each snow category. Tb combination rules from LST (Table 2) were used to compare the classification performances between the two approaches.

Table 2. LST approach used for snow classification (from McFarland and Neale [3]).

Tb Combination Rule	Snow Condition		
	Dry	Wet	Refrozen
T22V - T19V	≤ 4	≥ 4	≤ 4
(T19V+T37V)/2 - (T19H+T37H)/2	> 4	> 9.8	> 4
T37V	> 225 ≤ 257	> 253 ≤ 268	≤ 225

Table 3. Performance comparison between ANN and LST approaches.

Snow Condition	Error Rate (%)	
	ANN	LST
Snow-free	3	3
Dry	5	14
Wet	9	100
Refrozen	0	100

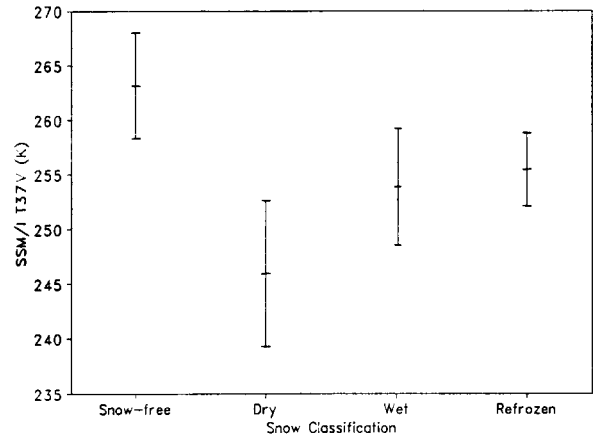

Fig. 2. 95% comparison intervals for the means of the T37V of different snow conditions in test data.

3. RESULTS AND DISCUSSIONS

Error rates of both approaches (Table 3) show that the ANN has a significant promise in identifying mountain snow conditions. The worse performance of the LST approach could be due to having evergreen forests and snow cover at mountain ranges. As seen in Fig. 2, for example, the 95% comparison intervals of SSM/I T37V means among dry, wet, and refrozen snow are overlapped by which there is no significant difference among the means. Theocratically, vegetation overlaying snow cover can affect passive microwave response of snow. As a result, spring wet or refrozen snow cannot be interpreted by LST snow rules (Table 2), which are developed only based on data over plains with non-dense vegetation [3].

4. CONCLUSIONS

The problem restricted the use of LST classification scheme to classify mountain snow cover in the form of dry, wet or refrozen is presented. This study indicates the potential of ANN supervised learning for the inversion of snow conditions from SSM/I measurements. Further improvement on the application of ANN for large-scale snow monitoring can be expected by using input and output pairs of training data derived from both plains and mountain regions with additional input of vegetation index.

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