NEURAL NETWORK INVERSION OF SNOW PARAMETERS BY FUSION OF SNOW HYDROLOGY PREDICTION AND SSM/I MICROWAVE SATELLITE MEASUREMENTS *

Yuankai Wang, Jenq-Neng Hwang, Chi-Te Chen, Leung Tsang
Department of Electrical Engineering, University of Washington, Seattle, WA 98195
Bart Nijssen, Dennis P. Lettenmaier
Department of Civil Engineering, University of Washington, Seattle, WA 98195

ABSTRACT

Inverse remote sensing problems are generally ill-posed. In this paper, we propose an approach, which integrates the dense media radiative transfer (DMRT) model, snow hydrology model, neural networks and SSM/I microwave measurements, to infer the snow depth. Four multilayer perceptrons (MLPs) were trained using the data from DMRT model. With the provision of initial guess from snow hydrology prediction, neural networks effectively invert the snow parameters based on SSM/I measurements. In addition, a prediction neural network is used to achieve adaptive learning rates and good initial estimate of snow depth for inversion. Result shows that our algorithm can effectively and accurately retrieve snow parameters from these highly nonlinear and many-to-one mappings.

1. INTRODUCTION

It is of great practical interest to realistically and efficiently infer the spatial distribution and time evolution of snow parameters (e.g., snow water equivalent, snow depth, snow grain size, etc.) from sensed measurements. One mechanism is to use the passive microwave brightness temperatures $\boldsymbol{m}$ to retrieve the snow parameters $\boldsymbol{x}$, which is of the general classes of inverse problems in remote sensing.

The inverse problems are difficult for the following reasons [1]. Firstly, the relationship between remote sensing measurements and the geophysical snow parameters is highly nonlinear. Secondly, the inverse mapping is often many-to-one, i.e., more than one set of parameters $\boldsymbol{x}$ could count for the set of measurements $\boldsymbol{m}$. Thirdly, the inversion problem is often in a form similar to that of a Fredholm equation of the first kind, making the inversion ill-conditioned. Finally, existing parameter retrieval algorithms [1,2] mainly consisted of matching a type of measurement to model predictions, while ignoring other available information [3]. Moreover, the brightness temperature measurements are known to be not only influenced by snow water equivalent, but also by snow grain size, snow temperature and snow density, which are not effectively modeled in the retrieving algorithms in the past [8].

In this paper, we developed a multi-parametric neural network inversion algorithm using multi-frequency and dual polarization measurements. In the inversion process, snow hydrology model provides initial estimates of the snow parameters for the trained neural network to iteratively calculate the snow parameters using SSM/I measurements. This inversion process is also facilitated by a prediction neural network, which regresses the past time evolution of snow parameters, to finetune the initial estimates from snow hydrology model and to speed up the inversion convergence by adaptively controlling the learning rates.

Section 2 of this paper presents the basics of neural network. Section 3 describes our inversion algorithm and the prediction neural network. Section 4 presents the simulation results, and conclusion is given in Section 5.

2. NEURAL NETWORK BASICS

In a multi-layer network, neurons are interconnected in a varying number of layers to provide greater computational complexity. By adjusting the weights, a neural network can be trained to perform a range of different input-output functions. Once the neural network has been trained, the

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network can be inverted to generate input vectors which would produce a desired output [1]. The inversion uses an idea similar to the back propagation algorithm, where error signals are back propagated to determine the inputs the manner in which to change so as to decrease the output error (see Figure 1). This process can be expressed by the following equation:

$$\boldsymbol{a}(0) \Leftarrow \boldsymbol{a}(0) + \Delta\boldsymbol{a}(0) = \boldsymbol{a}(0) - \eta\frac{\partial E}{\partial\boldsymbol{a}(0)}, \quad (1)$$

where E is the mean squared error between the desired outputs $\boldsymbol{t}$ and the actual outputs $\boldsymbol{a}(\boldsymbol{L})$, and η is the learning rate.

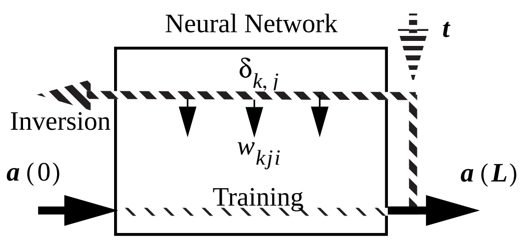

Figure 1. Illustration of training and inversion of a neural network. The performance of inversion highly depends on the initial estimate of inputs.

3. INVERSION DRIVEN BY SNOW HYDROLOGY

The objective of our approach is to make use of more relevant information to improve the inversion accuracy. Figure 2 depicts how the DMRT model, snow hydrology model and neural network are integrated to work.

3.1 Training with DMRT Data

In passive microwave remote sensing, the microwave emission from the ground surface and the snowpack is measured. The radiation is scattered and absorbed by the snowpack as function of its temperature, depth, grain size, fractional volume, and other parameters. The model used to simulate the microwave interaction with the snowpack is the dense media radiative transfer (DMRT) model [6]. Unlike the traditional radiative transfer models, the DMRT takes into account the dependency of scattering upon relative particle positions which is important in a dense media such as snow. In this framework, the model incorporates a particle size distribution using a modified gamma distribution. Therefore, a medium contains particles with different sizes, such as snow, can be accounted for. The model accounts for scattering by the snow particles as well as the interaction at the snow/soil interface and the snow/air interface.

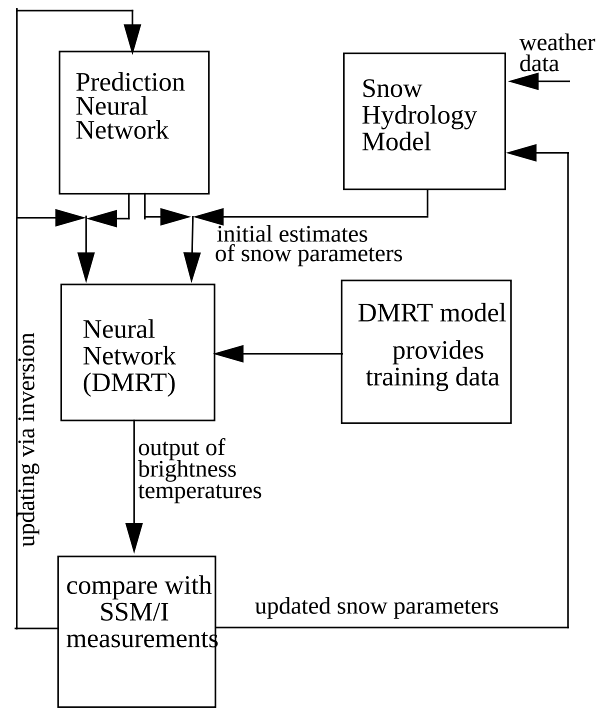

Figure 2. System block

The training data from DMRT model contains 7 inputs (snow depth, snow temperature, grain size, fractional volume, roughness polarization, maximum grain size, and ground permittivity) and 4 outputs (brightness temperatures for 19GHz vertical polarization, 19GHz horizontal polarization, 37GHz vertical polarization, and 37GHz horizontal polarization). Based on the dynamic ranges of snow depth, four neural networks were trained through the back propagation algorithm, and each network is in charge of one segment of DMRT model with different snow depth range.

3.2 Incorporation with Snow Model

The snow hydrology model was originally developed as part of the Distributed Hydrology-Soil-Vegetation Model (DHSVM) [5,8]. Snow accumulation and melt are simulated using a two-layer energy-balance model that explicitly incorporates the effects of topography and vegetation cover on energy exchange at the snow surface [7]. During melt conditions the snow pack is assumed isothermal at 0˚C. The model accounts for net radiation, sensible and latent heat exchange, and the energy advected by rain. Precipitation below a threshold temperature is assumed to be snow, which is added to the amount of water stored in the snow pack. The model accounts for the cold content of the snow pack, which must be satisfied before melt can occur.

The snow hydrology model also makes use of topographical and meteorological data, the later of which includes precipitation, air temperature, humidity, wind speed, incoming shortwave radiation, and incoming longwave radiation. For the current application to the sites in the Northern Hemisphere we used the surface meteorological data supplied by NASDA, augmented with historical station data from NCAR (NCAR dataset: *ds512 CAC Global CEAS Summary of Day/Month Obs, 1979-cont*).

With the initial estimates for snow parameters from snow hydrology model, the trained neural network predicts the brightness temperatures which are then compared with SSM/I measurements, and the difference is back propagated to adjust the snow parameters. The neural network iterative inversion executes until the snow parameters converge [2,9]. We then use these updated snow parameters as inputs to the snow hydrology model and move on to the next time step. With the combining runs of both models, we get the spatial distribution and time evolution of snow water equivalent.

3.3 Prediction Neural Network

In the iterative inversion process, it is of great importance to choose appropriate learning rates for inputs to expedite convergence. Moreover, good initial estimates for snow parameters, especially for snow depth, is helpful to the inversion, especially to maintain the continuity of the inverted snow parameters. To achieve this objective, a prediction neural network is used.

The prediction neural network was trained with ground truth of snow depth regularly sampled at given stations. Given the time series of ground truth $\{x_n\}$, the prediction neural network is trained to predict x_n, based on the past 6 data, i.e., $\{x_{n-1}, x_{n-2}, \ldots, x_{n-6}\}$. During the inversion of snow parameters at some regions, we keep a record of inverted snow depth for the designated prediction neural network, which is trained by the ground truth data from the station near the center of the region. With this record as the inputs to prediction neural network, the output gives the predicted snow depth $x_{prediction}$. Note that, we also have a snow depth from snow hydrology model $x_{hydrology}$, we can then construct the initial estimate of snow depth x_{init}, as the weighted sum of them:

$$x_{init} = w_p x_{prediction} + (1 - w_p) x_{hydrology}, \quad (2)$$

where w_p is a user defined constant. Only through this combination of information, we can ensure a reliable initial estimate of snow depth.

A relative error e_x is computed to determine the learning rate:

$$e_x = \frac{|x_{hydrology} - x_{prediction}|}{x_{prediction}} . \quad (3)$$

If it is greater than a given threshold, we set the learning rate to a larger value; otherwise, we set to a smaller value. This adaptive learning rate determination improves the convergence speed of snow parameter inversion.

4. SIMULATION RESULTS

Our algorithm has been applied to stations in the Northern Hemisphere, and results agree quite well with the ground truth. To verify the usefulness of our algorithm, we extensively compare the performance under three situations:

(1) running only the snow hydrology model itself;
(2) running the snow hydrology model and the neural network inversion without using the prediction neural networks;
(3) running the snow hydrology model and the neural network inversion with the use of the prediction neural network.

Figure 3 shows the snow depth retrieving results over Alaska-USA (station ID: 70231, Mcgrath) for winter of 1994-1995. To quantitatively compare the performance of all methods, we define the average percentage error as:

$$Error = \frac{1}{N} \sum_{i=1}^{N} \frac{|d_{true} - d_{predict}|}{|d_{true}|} \times 100\ \%, \quad (4)$$

$$\text{when} \quad d_{true} > 5cm,$$

where d_{true} is the ground truth snow depth data, and $d_{predict}$ is the result under different situations. The average percentage errors are also included in Figure 3.

From the curves, we can see that snow hydrology model captures the gross characteristics of the snow depth time evolution. Neural network inversion without prediction was found to enhance the performance, and inversion with prediction could give further improvement, which cuts the percentage error from 24.15% (Situation 1) and 14.42% (Situation 2) to 11.51%.

5. CONCLUSION

Through the incorporation of snow hydrology model with the SSM/I microwave satellite measurements, we make use of information relevant to the inverse remote sensing problem. The DMRT model takes into account the dependency of scattering upon relative particle positions which is important in a dense media such as snow. Snow hydrology model introduces other information, such as topographical and meteorological data, which are helpful to narrow down the solutions in many-to-one inverse problems. The neural network training well approximates the nonlinear relations between snow parameters and brightness temperature measurements, and the prediction from the past information (snow depth) further improves the retrieving performance.

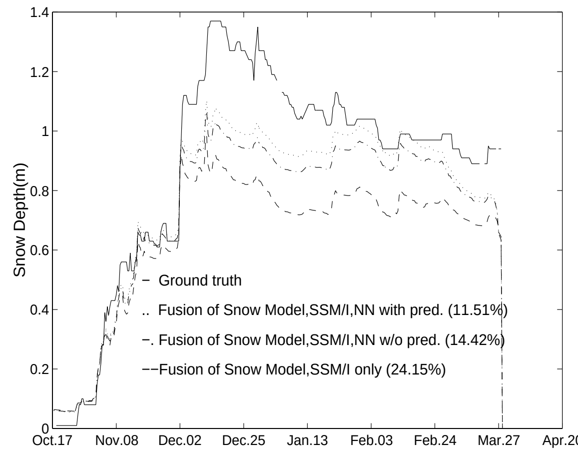

Figure 3. Time evolution of snow depth in station 70231

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