APPLICATION OF AN ARTIFICIAL NEURAL NETWORK IN CANOPY SCATTERING INVERSION

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Abstract

Because of their recent success in other inversion tasks [Ishimaru, 1990] application of an artificial neural network to the development of an inversion algorithm for radar scattering from vegetation canopies is considered. The inputs to the neural network are the expected polarimetric backscatter from specific canopies, while the outputs are the desired parameters, such as tree height, crown thickness, leaf density, etc.

Two special cases were examined: (1) inversion of MIMICS given Aspen stands of different ages; (2) inversion of measured data from the Duke forest Loblolly pine stands. The MIMICS inversion shows that neural networks are capable of accurately inverting some parameters of such a complicated model. The implication is that once MIMICS is made to model the radar data for a specific application, then inversion of the radar data may be accomplished. The measured data inversion shows that, even without a model such as MIMICS, one may train a neural network to invert several parameters of interest.

1 Purpose

The objective of this paper is the development of an efficient algorithm permitting inversion of polarimetric radar measurements for vegetation and underlying layer parameters. This process is not straightforward because canopy scattering models are complicated functions of the desired biophysical parameters. In particular, for a classified radar image, one would like to be able to find the characteristics for a particular stand in a particular image. In this paper the classification step is assumed to have been accomplished already. Hence, we have, at best, multifrequency and multipolarization data averaged over a stand at effectively a single incidence angle. Our inversion will deal with this set of data as the likely inputs.

In the past few years, artificial neural networks have been applied to several types of remote sensing problems [eg. Ishimaru, 1990]. Neural networks offer two major advances over other inversion approaches, such as the statistical and optimization methods. The first is the massive parallelism used in neural networks, and the second advantage is that the algorithms for the neural network are very general, allowing it to be used as a black box for any desired model or sets of input-output data.

This paper shows the application of this idea to a very small subset of all possible canopies: (1) Aspen stands modeled with MIMICS [Ulaby, et al., 1988], and (2) measured Loblolly pine stands. Inversion of several of the parameters that are used to describe these stands is presented. The parameters, in the case of the Aspen stands are: crown thickness, leaf number density, primary branch number density (thick branches), secondary branch number density (thinner branches), average trunk diameter, average trunk height, leaf diameter, and the complex dielectric constant (ϵ_r) of the trunk and branches at L and C bands. These parameters were chosen because they vary the most in the two Aspen stands that were measured. The parameters, in the case of the Loblolly stands are: trunk number density, average trunk diameter, and average trunk height. There are so few in comparison to the Aspen stands because of the lack of a complete set of ground truth for all 53 Loblolly stands.

2 Method

The method used in this paper can be broken into two main tasks: (1) generation of the appropriate training data, and (2) development of a neural network with the appropriate architecture, and the use of that network with test data. For the Aspen stands, the program MIMICS [Ulaby, et al., 1988] was used to generate the training data given the ground truth data, while the data as measured by the JPL AirSAR was used for the Loblolly stands. A widely-available neural network software package [McClelland and Rumelhart, 1988] was chosen to implement the inversion algorithm.

2.1 Modeling Aspens with MIMICS

The generation of the appropriate test data started with ground truth measurements of two Aspen stands for which polarimetric measurements had simultaneously been collected. These two Aspen stands were chosen for three reasons:

1. They were significantly different in age, giving a significant difference in many of the ground truth parameters, as well as in the polarimetric radar backscattered signals;
2. They were predominantly Aspen, rather than a complex mixture of different types of trees;
3. Each was relatively uniform in age throughout the stand.

The next step was to run MIMICS four times: for each of the two stands, at L- and C-bands (wavelengths of 24 cm and 5.66 cm, respectively). This was an iterative process because some of the canopy parameters were not precisely known. Once a believable set of input parameters was established for each stand at each frequency, three "interpolated" stands were created by linearly interpolating the 9 or so parameters that changed the most between the two stands. In this way, five stands of varying ages were generated, along with the expected polarimetric radar backscatter at the two frequencies, and for eleven different incidence angles (20° – 70°, by 5°). This gave a total of: 5 stands × 11 incidence angles = 55 training sets.

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2.2 Neural Network design: Aspen

This neural network was designed to use as input the incidence angle, and the polarimetric radar backscattered terms (hh, vv and hv in dB), at L and C band. Also included were ratios of some of these terms. Specifically, the inputs consisted of the following 10 real numbers:

- Incidence angle, degrees,
- σ^0_{hh}(L band), σ^0_{vv}(L band), σ^0_{hv}(L band),
- σ^0_{hh}(C band), σ^0_{vv}(C band), σ^0_{hv}(C band),
- $\frac{\sigma^0_{hh}\text{ (L band)}}{\sigma^0_{hh}\text{ (C band)}}, \frac{\sigma^0_{vv}\text{ (L band)}}{\sigma^0_{vv}\text{ (C band)}}, \frac{\sigma^0_{hv}\text{ (L band)}}{\sigma^0_{hv}\text{ (C band)}}$

The outputs consisted of the nine parameters mentioned in section one, using only the real parts of the dielectric constants, because there was so little variability in the imaginary part in the five stands used.

2.3 Neural Network design: Loblolly

This neural network was designed in a slightly different manner than that for the Aspen stands. The inputs consisted of ten real numbers: incidence angle, and the polarimetric backscattered terms (hh, vv, and hv in dB) at P, L, and C bands (wavelength of 66 cm, 24 cm, 5.66 cm, respectively). The outputs were the three real parameters mentioned in section one: trunk number density, average trunk diameter, and average trunk height. It was felt that with so few outputs the ratios, as used in section 2.2, were not necessary.

2.4 General Neural Network considerations

The neural network was designed to work with real numbers from zero through one, however, it does poorly when it must learn numbers near the extremes of this range, hence all inputs and outputs have been scaled to fit between 0.1 and 0.9.

The architecture of the network is largely governed by the constraints of the backpropagation algorithm [McClelland and Rumelhart, 1988]. This allows for several layers of several neurons, with each layer connecting fully to the adjacent layers, and no other layers, with different multiplication factors (or weights, w_k) connecting each pair of nodes. The inputs are presented to the input layer, with the outputs available on the output layer, and any number of so-called hidden layers may intervene (Fig. 1). The input and output layers are fully specified by our requirements as stated previously, but the number and size of the hidden layes are free parameters. After trying various numbers and sizes of hidden layers, a network that gave the least error with the least amount of training was chosen. The number of hidden layers in each of the resultant networks was 3, with 33 neurons (or nodes) in each layer for the Aspen network, and 30 neurons per layer for the Loblolly network.

A number of other parameters control the performance of the network while it is learning, and they were set as follows:

- **learning rate:** A measure of how much to change a given weight when an error is detected. Slow is near zero, with the rate increasing as this number increases , we used 0.1.
- **momentum:** A measure of how much the previous cycle of learning will affect this cycle. Small effect is near zero, large effect is near 1; 0.9 was used here.

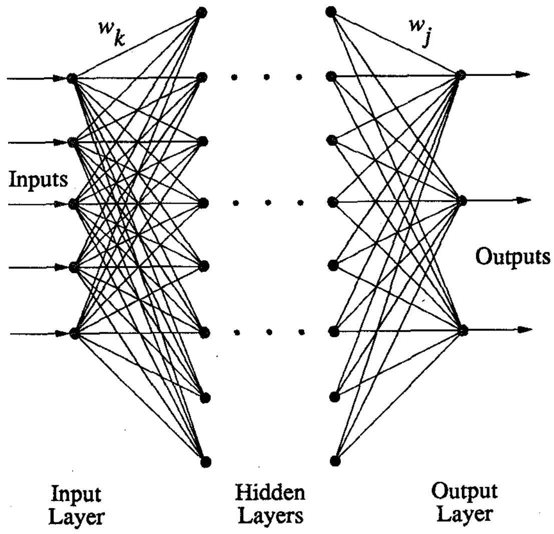

Figure 1: A typical multi-layer perceptron (MLP) type of neural network, the type that is used in this paper. Note that two of the many weights are labeled.

A description of the back propagation algorithm for learning in this type of neural network is beyond the scope of this paper. Numerous introductory papers and books exist on the subject and should be consulted for a detailed understanding of the above parameters and the learning process in general [Rumelhart and McClelland, 1986; Lippmann, 1987].

The learning process proceeds as follows:

1. A file is prepared containing the training sets,
2. The neural network architecture is defined and built,
3. The weights specifying the connection strengths between every pair of neurons are randomized,
4. The training sets are presented in a random order, but all are presented once for each cycle,
5. The weights slowly adapt to produce the desired output,
6. The weights are saved when the error is low enough.

Next, the testing process:

1. The network is restarted, with learning turned off, and the previously-saved weights are loaded,
2. A file with the test sets is then read and presented to the network,
3. The detailed results of the test sets are displayed with expected and actual outputs, and with the errors.

The results of this testing process are presented in the next section.

3 Results

Both attempts at inversion worked well for some parameters and poorly for others. This section presents the results for each of the two attempts.

3.1 Inversion of Aspen stand parameters

The purpose here was to show that a neural network can invert the modled results of MIMICS. This means that after the neural network is trained with MIMICS input/output patterns from several different Aspen stands, it is then presented with a new Aspen stand and asked to invert it. Comparison with the MIM-

ICS input parameters for each stand then serves to quantify the performance of the neural network inversion. The Aspen neural network was trained for a total of 12,914 cycles before being tested, the results of which are presented here.

The range of parameters for the stands is shown in Table 1, along with the actual parameters for the test stand. The test stand parameters are between those of stands 2 and 3, with stands 1 and 5 representing the limits of these parameters. For the 55 test input patterns the errors were tabulated for each parameter and the results are presented in Table 2. The worst and average absolute percentage error are shown for each parameter and it is clear that the inversion worked very well for every parameter of interest, the worst error of 2.28% occurring for leaf number density when the network estimated 84 leaves/m^3 compared to the 82 that was used as the input to MIMICS.

Table 1: Range of parameters for Aspen stands.

Parameter	1	5	test
Crown Thickness (m)	6.90	11.50	8.63
Leaf # density / m^3	48.46	138.74	82.32
Leaf diameter (cm)	6.76	4.59	5.95
Primary branch # density / m^3	1.35	2.70	1.86
Secondary branch # density / m^3	13.50	27.00	18.60
Avg Trunk Diameter (cm)	14.50	32.50	21.30
Avg Trunk Height (m)	14.16	30.20	20.18
Trunk and Branch Re.ϵ_r, L band	31.86	41.76	35.55
Trunk and Branch Re.ϵ_r, C band	22.23	30.19	25.22

Table 2: Percent error in parameters for test Aspen stand.

Parameter	worst	average
Crown Thickness (m)	1.16	0.61
Leaf # density / m^3	2.28	1.29
Leaf diameter (cm)	1.00	0.61
Primary branch # density / m^3	1.61	0.81
Secondary branch # density / m^3	1.61	0.83
Avg Trunk Diameter (cm)	1.84	0.84
Avg Trunk Height (m)	1.67	0.91
Trunk and Branch Re.ϵ_r, L band	0.63	0.40
Trunk and Branch Re.ϵ_r, C band	0.74	0.34

3.2 Inversion of Loblolly stand parameters

The purpose here was to show that a neural network can invert measured data *without* the need for a model, such as MIMICS. This means that after the neural network is trained with the measured backscatter for the 53 Loblolly stands in a particular JPL AirSAR image, it is then presented with the measured backscatter for the same 53 Loblolly stands but at a different time of day and different incidence angles and asked to invert each of them. Comparison with the known ground truth data then serves to quantify the performance of the neural network inversion. The Loblolly neural network was trained for a total of 19,160 cycles before being tested, the results of which are presented here.

The range of parameters for the stands are shown in Table 3. For the 53 test stands the errors are tabulated in Table 4. The worst and average absolute percentage error are shown for each parameter, and it is clear that the neural network could not successfully invert trunk density, but inverted trunk diameter and height reasonably well, with a worst-case error of 12% and an average error of 2%.

Table 3: Range of parameters for Loblolly stands.

Parameter	min	max
Trunk # density / m^2	0.0067	0.227
Avg Trunk Diam (cm)	6.8	45.1
Avg Trunk Height (m)	8.9	39.6

Table 4: Percent error in parameters for test Loblolly stands.

Parameter	worst	average
Trunk # density / m^2	105.3	11.9
Avg Trunk Diam (cm)	12.2	2.2
Avg Trunk Height (m)	9.9	2.1

4 Conclusions

We have shown that an accurate inversion of several important parameters of interest in canopy scattering can be obtained from multi-frequency polarimetric radar data or through the use of a neural network trained with MIMICS output. This has been shown for two specific cases only, but may be easily extended to other types of trees. No attempt was made to invert every possible parameter, but future work must be directed toward that goal in order to truly invert remotely-sensed data. The extension to mixed forest types, and the extraction of other parameters is not straightforward and further effort needs to be made in order to obtain better inversions over a greater variety of forest stand types.

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