Ground-Based Scatterometer Measurements and Inversion of Surface Parameters by Using Neural Networks

Mingquan Jia*, Ling Tong
School of Automation, University of Electronic Science and Technology of China (UESTC), Chengdu in Sichuan Province, 610054, China
*jiamingquan@163.com

Abstract—In this study, a multi-band FM-CW ground-based scatterometer is used to measure the backscattering coefficient of bare soil surface. Combined with the neural network (NN) and the advanced integrated equation model (AIEM), it inverses all the soil parameters, including dielectric constant, root mean square (RMS) height and correlation length. According to different data sources, the NN can be constituted as different input-output mapping mode. The NN is trained by using theoretical data that are simulated by the AIEM. The measured data are an input to the NN to inverse the soil parameters. The inversion results have a better consistency with the sampling correlation length. The NN achieves two different training patterns used to train this network are developed by using the AIEM model. In this way we can choose different training patterns according to the practice radar measurements, and also control the content and ranges of the surface parameters. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, which can be used to inverse the surface parameters directly. Finally, the scatterometer data are an input to the trained NN to inverse the soil parameters, including soil moisture, RMS height and correlation length. The NN achieves two different training patterns of soil parameters inversion. A comparison of the theoretical data that are simulated by the AIEM. The measured data are an input to the NN to inverse the soil parameters. The inversion results have a better consistency with the sampling correlation length. The NN achieves two different training patterns used to train this network are developed by using the AIEM model. In this way we can choose different training patterns according to the practice radar measurements, and also control the content and ranges of the surface parameters. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, which can be used to inverse the surface parameters directly. Finally, the scatterometer data are an input to the trained NN to inverse the soil parameters, including soil moisture, RMS height and correlation length. The NN achieves two different training patterns of soil parameters inversion. A comparison of the theoretical data that are simulated by the AIEM. The measured data are an input to the NN to inverse the soil parameters. The inversion results have a better consistency with the sampling correlation length. The NN achieves two different training patterns used to train this network are developed by using the AIEM model. In this way we can choose different training patterns according to the practice radar measurements, and also control the content and ranges of the surface parameters. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, which can be used to inverse the surface parameters directly. Finally, the scatterometer data are an input to the trained NN to inverse the soil parameters, including soil moisture, RMS height and correlation length. The NN achieves two different training patterns of soil parameters inversion. A comparison of the
actual measurement data and the inversion results shows that the NN inversion method has a high accuracy. This approach gives one more option which may be useful for the inversion of soil moisture and surface roughness statistics.

II. GROUND-BASED SCATTEROMETER MEASURING SYSTEM AND MEASURING DATA

A. Scatterometer Measurement System

The ground-based radar scatterometer (GBRS) was constructed by University of Electronic Science and Technology of China (UESTC) [12]. The sensor is carried by the radar of FM-CW. The dual-antenna system maintains the monostatic radar performance, which can measure the backscattering coefficient among -45 and 20 dB, with target distance from 10 to 100 m. The microwave scattering measurement system is configured with four different pairs of parabolic antennas, and each of the antenna has a transmitting channel illuminating the soil with a linearly (h or v) polarized electromagnetic wave and a receiving channel detecting the linearly polarized (h or v) wave backscattered from the target. The system can measure full-polarizations. The GBRS system has a tilt and azimuth scanning capability of the ground-based radar platform; it can transform the incidence angle or pitch angle range from 0° to 90°, azimuth angle range from 0° to 360°. The system is equipped with four operating frequency which are L-band (center frequency of 2 GHz), S-band (center frequency of 3.1 GHz), C-band (center frequency of 5.3 GHz), X-band (center frequency of 10 GHz).

![Figure 1. The picture of bare soil measurement site](image)

The computer and scatterometer are connected with a standard serial interface RS232 communication cable, whose communication distance can reach 15 m. The bare soil measurement is shown in Figure 1. The computer software can achieve continuous and automatic measurements in different incidence angles. All measured data are automatically saved in the database. The measuring procedure is described as follows.

1) Install support structure of the scatterometer, and connect the cable to the system for power.

2) Input the measurement mode (including continuous, single, step scan, angle range) from the host computer interface to the numerical control equipment by the host computer in order to control the turntable of antennas, transmitters, receivers, calibration switches.

3) The scatterometer measures the distance between antenna and target by using spectral analysis techniques. Then it uploads target echo energy, the current angle of incidence, and all other information.

4) All information is displayed in the host computer interface, and stored on the hard drive of host computer.

First, internal calibration of the scatterometer is carried. A 27-m coaxial line is used as a delay line, and a step attenuator is used as attenuation for the internal calibration procedure. According to the radar equation and internal calibration procedures [2], the backscattering coefficients in the work state were calculated as the following expression:

$$\sigma_i = \frac{P_m}{P_m} \frac{L_m}{L_m} \frac{L_v}{L_v} \frac{\sigma_v}{\sigma_v} \frac{4R^2}{\pi\beta_v \beta_H}$$

where $\sigma_i$ is the backscattering coefficient, R is the distance from the antenna to the observed target, P is the distance of receiver channel controllable attenuator, and L is the output power of scatterometer. Subscript m, c, and i are measurement status, external calibration status, and calibration status, respectively; $\beta_v$ is vertical plane beam width of antenna, and $\beta_H$ is horizontal plane beam width, $\theta$ is incidence angle.

To complete external calibration polarimetric scatterometer, the experiment obtains full polarimetric data from known targets whose scattering matrices have independent eigenvectors. The experiments are designed in the real field test site to achieve accurate external polarimetric calibration. First, we hang two metal spheres (diameters with 469mm and 580mm) in the air by using hydraulic lifting device to ensure no other objects within five meters radius of each ball. The metal spheres are hung by very small non-metallic wire, whose scattered signal can be ignored. Antenna beam covers the metal sphere, measures it, and scan multiple incidence angles within a certain range. The maximum value is the scattering coefficient of each metal sphere. Second, the calibration of the scatterometer is examined by measuring scattering matrices of different sizes metal spheres at each band [13]. Then the calibrated elements of the scattering matrix are compared with the sphere theoretical values. Finally, in order to verify the accuracy of the calibration, the large metal sphere is used for calibration target, and the small metal sphere is employed as test target. The result shows that the measured values of the co-polarized are within 1 dB of the theoretical results, and the measured effective polarization isolation for the smaller metal sphere is less than 30 dB at each band.

To acquire several independent samples, the scatterometer is mounted on a pivoting platform. At least 36 independent samples are averaged in each measurement, to ensure a 90% confidence interval of 1 dB. The number of independent samples contained in a footprint is designed in the laboratory. It is computed from the following expression:

$$N_i \approx 2h\beta_B \tan \theta / (c \cos \theta)$$

where, $N_i$ is the number of independent samples, h is height from antenna to ground, $\beta$ is beam width, $\beta$ is modulation band of the scatterometer, there are different $\beta$ for different bands, and $\theta$ is the antenna incidence. For example,
at 12.5-m height and 45° incidence angle, the C-band scatterometer footprint contains about 11.2 resolution cells. The required independent samples are achieved by acquiring 20 nonoverlapping footprints and pivoting the antenna around a vertical axis. In this case the total number of independent sampling is more than 220 resolution cells. Therefore, the number of independent is from 60 (at incidence angle of 20°) to 5000 (at incidence angle of 80°) at C-band. The other bands are similar to this. After completing the internal and external calibration and statistical average of independent samples, the overall measurement error of the system is less than ±1 dB.

B. Measurement Data

1) The Backscattering Coefficient

In order to get the backscattering coefficient of soil, we carried out a large number of field measurements experiments in October, 2009. The test site was located at an experimental of UESTC field (103°32'24"E, 30°24'11"N) Qionglai County, Chengdu, Sichuan province, China, and the object was the bare soil without sowing of wheat. The data of scatterometer measurement included L, S, C, X band, HH, HV, VH, VV polarization, and the incident angle from 0° to 90° step 1°.

Figure 2 shows the measured polarimetric backscattering coefficient of L/S/C/X-band curve as a function of the incident angle. In theory, microwave backscatter at cross-polarizations, i.e., HV and VH, is equivalent for the same target. Indeed, the overall correlation between the HV and VH coefficients is 1 -to-1 line for all frequencies and incident angles. Therefore, data from both cross-polarizations are averaged for each set of measurements.

![Figure 2. Multi-band scatterometer with different polarization measurements](image)

Two graphs are shown, one for L-band and another for S-band. The graphs display the backscattering coefficient (in dB) as a function of the incidence angle (in degrees). The coefficient is plotted for HH, VV, and Cross-polarizations. The data is shown for angles ranging from 0° to 90°, with a step of 1°.

We can see from the Figure 2 that backscattering coefficient is decreasing as the angle is increasing significantly from 0° to 10° and also from 60° to 80°. A smooth in backscatter is observed from 10° to 60°, and the higher the frequency is, the smaller the change will be. For instance, L-band decreases 10 dB, but X-band decreases only 2dB from 10° to 60°. There is a certain degree undulation for the bands that have higher frequency including C and X-band, which is because that, when the wavelength is shorter, the roughness will have a greater impact on the backscatter coefficient. The backscattering coefficient at VV polarization is higher than that at other polarizations for each band, and is consistent with the simulation results of integral equation method (IEM) [4]. The value of the difference VV and HH polarizations is less than 2dB. The cross-polarization backscatter is similar to the co-polarization that versus incidence angles, but the backscatter value is smaller, at about 6dB (L-band), 8dB (S-band), 9dB (C-band) and 12dB (X-band).

2) The Soil Parameters

Figure 3 (a) (b) and (c) shows the measurement picture of soil parameters, which include roughness, soil sample, soil moisture and dielectric constant. Soil moisture content is measured by using the gravimetric method [2]. The resulting gravimetric moisture content was transformed into volumetric moisture content through multiplication by the soil bulk density. In the experimental area, the moisture is 12.3 % to an average of more than 20 soil samples. The type of soil is clay, which accounts about 50%. Sand takes up 15%. The other types are 35%. The transmission/reflection method is used to measure the soil dielectric constant that based on vector network analyzer [13]. The soil dielectric constant is 5 in using this method. Soil roughness profile is measured at the same time. A 1-m-long needle profiler, with a horizontal resolution of 0.9 cm and an accuracy of about 0.2 cm in the vertical direction [14], is used to measure soil roughness along directions parallel and perpendicular. The average profile RMS height is 1.56 cm, and the correlation length is 15.5 cm. The correlation function is exponentially distributed.

![Figure 3. Measurement of soil parameters: (a) soil roughness; (b) soil sample; (c) soil moisture and dielectric constant](image)

III. SOIL MODEL AND NEURAL NETWORK TRAINING

A. BP Neural Network Optimization

Back Propagation (BP) network was applied to the widespread and important neural network. NN theory has proved that BP has a strong non-linear mapping and generalization ability. In the Matlab software, when using NN training to improve the training efficiency and accuracy, we need to notice the following aspects.

1) A Regulation of Training Data

Sample data value (P) and target (T) carried out pre-normalized contribution to the stability of BP network training. In order to avoid over-concentration of data, and improve
speed of training, the data were regulated at the range of [0, 1] in this article.

2) To Determine the Network Structure

NN theory theorem Kolmogorov has proved that the three-BP network can approximate any function by full study. However, the experiment showed that the increase of the network layers can improve the training accuracy, so this article used 4 or 5-layer structure of the network for different situations. The three parameters of inversion determined three output nodes. The input layer nodes were the best to set 20 after repeated training. Hidden nodes were determined by the following experience formula:

\[ s = \left( 0.43m + 0.12n^2 + 2.54m + 0.77n + 0.35 \right)^{0.5} + 0.51 \]  

where: s is the hidden nodes, m is the input layer nodes, and n is the output layer nodes. In this paper, we use the network structure of 4 layers (20, s+2, s, 3), or 5 layers (20, s+2, s, s-2, 3).

3) Choice Learning Algorithm

Basic BP algorithm makes the MSE tend to minimize by using gradient descent. However, it has a slow pace of convergence and a local minimum in practice. Matlab7.0 NN toolbox provides a variety of fast learning algorithms. The most representative ones are five algorithms: traingdx, trainrp, trainscg, trainoss and trainlm. Experiments show that there is a most representative ones are five algorithms: traingdx, trainrp, trainscg, trainoss and trainlm. Experiments show that there is a different limits error for different learning algorithm, so this article uses trainlm for it has the best training accuracy.

In TABLE 1, all the training data are simulated by the AIEM scattering model. Before training, the effective range of surface parameters is chosen based on the actual situation including the soil dielectric constant \( \varepsilon \), the surface RMS height s and correlation of l. Finally, we use the backscattering coefficient simulated by AIEM to combine into a training data set as the table form.

Next, we choose two ways of training and inversion, including full-polarization mode \( \hat{P} = (\sigma_{hh}, \sigma_{vv}, \sigma_{cross}, \theta) \), and dual-polarization, dual-channel mode \( \hat{P} = [\sigma_{hh}, \sigma_{vv}, \sigma_{cross}, \theta] \).

C. The Results of Training and Error

1) Full-polarization Mode

The training data P is selected HH, VV and cross polarization at S-band (3.1GHz), and the incident angle is from 10° to 70° step 5°. The ranges of output parameters T are set. Dielectric constant \( \varepsilon \) is from 5mm to 35mm step 3mm. RMS height s is from 8mm to 35mm step 3mm. And correlation length is from 30mm to 170mm step 10mm. Then the full-polarization mode is trained by using these data that are simulated by the AIEM. After completing the training of network, the NN has achieved correspondence from full polarization data to the soil parameters. Figure 4 shows the soil parameter inversion value.

In Figure 4, the three straight lines are input values of the AIEM, and the AIEM output values are the NN input. They get the output value express to three curves with symbols. As it can be seen from Figure 4, the inversion value of NN is very close to the input values of the AIEM. This means that the NN has very good correspondence from full polarization data to the soil parameters. It is shown that the NN can be used to invert three soil parameters by providing full polarization data.

2) Dual-polarization and Dual Frequency Mode

Two-frequency has been selected as 3.1GHz and 5.3GHz which are scatterometer frequency of S-band and C-band. Polarization is HH and VV. Other parameter set is the same to full-polarization mode. The training data for input data set P and output data set T are generated by the AIEM. Then we use these data to train the BP NN. After completing the training of network, the NN can be used to invert the soil parameters. Training error decline curve in the process and inversion results of different angles have been shown in Figure 5.

We can see the error decline curve quickly but reach a high precision in this training mode from Figure 5-a. Figure 5-b/c/d

---

shows the results of NN inversion, which includes ε, s and l. The error of inversion is less than 2%, so it is feasible to use NN achieve parameters inversion of high-precision. In addition, the experiment shows that reducing the range of parameters can increase training speed and accuracy. Therefore, the range of surface parameters can be reduced appropriately according to the actual situation.

As can be seen from Figure 4, the inversion value from NN is very close to the measured values. In particular, the error of soil water content and correlation length is less than 15%. The each inversion value is very stable from 35° to 70° which means that the NN provides a greater range of adaptation for incidence angle that covers most of the satellite SAR data. The curves have large fluctuations in small incidence angle (20°-35°) for Figure 6 (a) (b) and (d). Co-polarization difference of AIEM is very little at small incidence angle, so little fluctuations of the measured value will cause large errors.

**B. Dual-polarization and Dual-frequency Mode**

The measuring data of HH and VV polarization at S-band and C-band are used to combine into the input array P: 

\[ P = [\sigma_{HH}, \sigma_{HV}, \sigma_{VV}, \sigma_{VH}, \sigma_{ref}, \sigma_{ref}, \theta] \]

The array input added into the trained NN is to inverse the three soil parameters at different incident angles, and the soil moisture is also got from the dielectric constant by using Top empirical formula [15]. Figure 7 shows the angular variation of the inversion value. As can be seen from Figure 7, the inversion parameters of dielectric constant and soil moisture are very stable at all incidence angles from 20° to 80°, but the curves of correlation length and RMS height have a certain fluctuations with the incidence angle, particularly at smaller angle (20°-40°). Little fluctuations of the measured value that include co-polarization difference and differences in band will also cause large errors. The error of soil water content of this mode is less than the full-polarization mode. It shows that more extensive data can provide higher accuracy, but may lead to greater instability, such as correlation length and RMS height. In addition, soil surface roughness is uneven at different angles and has different magnifications for inversion error. It is also a factor that leads to fluctuations of curve.

Comparing the inversion results with the data, we find that the dielectric constant, RMS height and correlation length are basically the same when the volatility of the curve accords with the fluctuations of the actual measurement data. It shows that the use of scatterometer data for inversing surface parameters is basically viable, and also shows that neural network inverse multi-parameters are effective. Actual measurements found that the roughness of different directions
may be quite different in that, one-dimensional AIEM can not completely reflect the relation between different direction roughnesses with the backscattering coefficient. So we need to study the two-dimensional model and the corresponding roughness characterization.

In addition, the results of the inversion of soil moisture have a lot of difference. The main reason is that, the top formula generally applies to the soil with larger sand content, but not the soil with larger clay content. We use Dobson semi-empirical formula to calculate [16]. When the soil moisture content is 12%, the value of relative dielectric constant is about 7, so it is consistent with the measured data. However, to complete the inversion of the formula Dobson, the imaginary part of dielectric constant value and the dielectric constant relate to the frequency are also needed.

To sum up, inversion accuracy mainly depends on four aspects, including the accuracy of the model simulate surface scattering, the training accuracy of NN, the measurement precision of backscattering coefficient and the measurement accuracy of surface parameters. In general, the inversion accuracy of neural network can be improved through setting the training algorithms and parameters, the measurement accuracy of scatterometer as well, and the direct measurement accuracy of the surface parameters can be ensured easily, so the final inversion accuracy mainly depends on the situation accuracy of model. As a result, it is very important to choose or build a better scattering model that can better simulate the actual surface scattering, especially for the objects that are unknown for the scattering mechanism.

V. CONCLUSIONS

In this paper, NN inversion is realized to all the soil parameters. The theoretical simulation and the experimental data are used to train and verify the BP network. First of all, a multi-band FM-CW ground-based scatterometer is used to measure the backscattering coefficient of bare soil surface. The system parameters of measurement include L/S/C/X-band, full-polarization and different incidence angle. The training data is simulated by using the AIEM model. According to different scattering data, the NN is divided into two different training patterns. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, and it can be used to inverse the surface parameters directly. Finally, by using S-band and C-band measurements data, the trained NN achieve the inversion of three soil parameters. A comparison of the actual measurement data and the inversion results show that the NN inversion method has a high accuracy. There are three following conclusions:

(1) Even though the surface parameters are unknown, it is possible to realize the full inversion of the bare soil moisture and surface roughness parameters by using the multi-polar and multi-band measurements at the same incident angle.

(2) At each training pattern, the trained NN can get an accurate mapping relation between the radar measurement and the surface parameters. So the inversion accuracy depends on the accuracy of the validity of the models upon which the training data are based on the AIEM and dielectric models.

(3) If the input data of NN training patterns want to use the multi-angle data, the soil surface must be very uniform to ensure that the measured of different incidence angle can be used as the same surface. When the same region has multiple SAR data that are from different incident angles, the surface parameters can be inversed by this training pattern.

In short, the NN method has high inversion speed and accuracy. Its inner mapping accuracy is precise enough to be applied in practice. It is an effective means combined with model simulation and ground-based scatterometer experiment to study microwave scattering mechanism. The parameters inversion study using measurement data has some reference value to extract parameters at large-scale of microwave remote sensing. However, the presence of vegetation make the radar return not necessarily attributed from the soil. In this case, the training data must be generated by the vegetation scattering model. Unfortunately, there is no vegetation model that can widely adapt to each planting. And vegetation model has more input parameters, including soil surface and vegetation parameters. To solve this problem, further study will concentrate on the scattering mechanism of crop vegetation by using the ground-based scatterometer and vegetation parameter inversion method of NN.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (No. 40871160 and No. 41071222), and the Inversion and Verification Project of Solid Surface Parameters Base on SAR.

REFERENCES


Mingquan JIA received the B.A. degrees from Xihua University in 2005 and M.S. degrees from the University of Electronic Science and Technology of China (UESTC) in 2008, and is currently pursuing a Ph.D. at UESTC since 2009. His current activities include mechanism of microwave remote sensing, microwave ground-based scattering measurement, SAR and SAR interferometry for disaster monitoring (including landslide surveying, snow-cover mapping, and monitoring of droughts and floods). Between 2007 and 2008, he worked on the model simulation and parameter inversion of soil and vegetation using microwave scattering measurements data. Between 2009 and 2010, his research included establish electromagnetic scattering model of soil, rice and wheat, and develop inversion method for geo- and biophysical parameter, and study polarization calibration techniques for scattering measurement system.

Now, his main involvement currently is in development scattering model and studying algorithms of information extraction from SAR image development of applications and the definition and implementation of related services in land surface deformation.

Ling TONG is a professor and vice president at School of Automation Engineering, University of Electronic Science and Technology. In 1985, she graduated from the Chengdu Institute of Telecommunication Engineering university, received her bachelor's degree. In 1988, she graduated from the University of Electronic Science and Technology, received her master's degree. From 1988 to 1995 engaged in the study of microwave and antenna measurements at Testing Technology Research Institute in China. Since 1995, her main involvement currently is in the mechanism of remote sensing, microwave remote sensing, microwave, millimeter-wave measurements, measurement data processing and information theory and other aspects of the study measurements.