NEURAL NETWORK AND FUZZY LOGIC FOR AN IMPROVED
SOIL MOISTURE ESTIMATION

Tarendra Lakhankar, PhD Student
Hosni Ghedira, Asst. Professor
Reza Khandilvardi, Professor
NOAA-CREST, City University of New York
New York 10031
tarendra@ce.ccny.cuny.edu
ghedira@ce.ccny.cuny.edu
khanbilvardi@ccny.cuny.edu

ABSTRACT

In the last two decades, various remote sensing techniques have been evaluated and proven to be a valuable source of information for different hydrological applications. Particularly, microwave remote sensing had been frequently used as alternative to traditional methods for estimating spatial soil moisture based on the large contrast between the dielectric properties of wet and dry soil. However, soil moisture response to microwave system from ground surface is mostly influenced by a variety of parameters such as land cover, vegetation density, and soil texture; which make the retrieval process more complex. In such conditions, non-parametric tools such as neural networks and fuzzy logic systems could have more potential in retrieving soil moisture from microwave sensors compared to traditional classification techniques. In this research, we have used Synthetic Aperture Radar data acquired by RADARSAT-1 satellite to retrieve the surface soil moisture along with vegetation-related information (vegetation optical depth and Normalized Difference Vegetation Index). The soil moisture data measured by Electronically Scanned Thinned Array Radiometer during the SGP97 campaign were used as truth data in the training and the validation processes. The performance of neural networks and fuzzy logic algorithms has been investigated by varying several parameters related to their structure and training processes. The preliminary results showed that for neural networks, the variation of the number of hidden layers and the number of neurons in each layer has no significant effect on classification accuracy. Concerning the fuzzy logic algorithm, the preliminary results showed that the cluster radius selection have a significant effect on classification accuracy. Further, the prediction made by neural network was found to be more accurate than fuzzy logic in several runs of the model, but the prediction made by fuzzy logic was more stable in nature.

INTRODUCTION

Knowing the spatial distribution of soil moisture in a watershed is essential for many hydrological processes, such as river flow forecasting resulting from rainfall storm events, planning, designing and scheduling of irrigation systems. The hydraulic conductivity and water intake capacity of soil during a rainfall event can be determined by the soil moisture content. Microwave remote sensing is currently gaining popularity for its ability to measure the spatial variation of soil moisture content in the upper layer of the soil surface under a variety of topographic and land cover conditions. Microwave remote sensing systems are used to measure soil moisture based on large contrast that exists between the dielectric constant values for dry and wet soils. The retrieval of soil moisture from microwaves systems is mostly influenced by the surface characteristics such as land cover, vegetation density, soil texture, topography, etc. Indeed having accurate information of the spatial distribution of vegetation improves the soil moisture retrieval from microwave data.

The soil moisture and the radar backscattering have a complicate and non-linear relationship mostly because the dynamics of soil moisture is influenced by a variety of environmental factors, e.g. surface roughness, soil texture, and, type and density of vegetation, etc. Previous studies have used linear regression models to represent the relationship between backscatter coefficient and soil moisture from a limited number of sample points (Ulaby et al. 1981; 1986; Bernard et al. 1982; Wood et al. 1993; Meade et al. 1999; Quesney et al. 2000; Moeremans et al. 2000; Gleen et al. 2003; Srivastava et al. 2003; Kasischke et al. 2003). This linear relationship is better correlated in the case of bare soil surface. However, the presence of vegetation reduces the sensitivity between the backscatter and soil moisture. These previous studies have shown that a single SAR channel cannot be considered a reliable source
to retrieve soil moisture by only considering its relationship with the dielectric constant. Indeed, it is imperative to consider other parameters such as NDVI, vegetation optical depth, soil texture, and land cover as an input to retrieve soil moisture. These variables cannot be simplified in small or empirical equations and need to have non-parametric tools like neural network (NN) and fuzzy logic (FL) to resolve the complex relationship that exists between soil moisture and microwave backscatter.

The application of neural network and fuzzy logic techniques as modeling tools are growing in the field of image classification. These tools are data driven, where a functional relationship is determined based on some training datasets. In addition, non-parametric methods do not require any assumptions to be made about the fitness of the data. Parametric models, however, are based on several statistical assumptions like the maximum likelihood method, where coefficients of linear and non-linear models are assumed as function of input variables. However, non-parametric models usually use non-statistical tools, such as artificial neural network and fuzzy logic methods.

The rapid increase of NN applications in remote sensing is due mainly to their ability to perform more accurately than other classification techniques. The other advantages of NN over conventional classification techniques are: the ability to handle data acquired at different level of measurement precision and its fast processing time after training the network (Foody and Arora, 1997). Multi-layer perceptron trained by back-propagation algorithm is the most common neural network used for image classification. This type of neural network have been successfully applied to image processing and have shown a great potential in the classification of different remotely sensed data (Paola and Schowengerdt, 1995).

Similarly, fuzzy logic technique has been used in many image classification applications. The fuzzy set theory, developed by Dr. Lotfi Zadeh in 1965, is a mathematical tool that deals with imprecise and vague data. The fuzzy set operations are based on a solid theoretical background. A fuzzy set generalized the Boolean set, by allowing partial membership in a set of values ranging from zero to one. The fuzzy logic technique based on fuzzy set theory has been applied in many areas where relationship between variables is not empirically defined. The advantage of fuzzy logic is its suitability in dealing with uncertainty and imprecision in a decision-making process, and thus offers a new approach for classifying remotely sensed images (Nedeljkovic, 2004).

This paper describes the algorithm development steps for soil moisture retrieval using non-parametric data driven modeling tools such as neural network and fuzzy logic to produce highly accurate soil moisture maps from active microwave data.

STUDY AREA AND INPUT DATA

The study area, located in Oklahoma, USA (97d35’W, 36d15’N), has a sub-humid and semi-arid climate with annual average rainfall of 750 mm. This area was selected based on the data availability from Southern Great plain mission (SGP97) conducted by NASA in 1997. This mission is a large, interdisciplinary field campaign performed over one-month period (18 June–17 July) with the objective to test formerly established soil-moisture retrieval algorithms (Jackson et al. 1999). The predominant vegetation covers are Pasture/Rangeland (~49%), wheat (~35%), summer legume (~5%), Alfalfa (~3%), and Forage (~4%). The active microwave, Synthetic Aperture Radar (SAR) data from RADARSAT-1 satellite was chosen for this study. With its only C-band channel, the effective penetration depth of RADARSAT beam is shallower than 5 cm for highly wet soil and deeper than 5 cm for dry soil (Ulaby et al. 1986). Two RADARSAT-1 images have been acquired on July 2nd and July 12th, 1997 by SCANSAR Narrow Mode. The high resolution SAR data (25m x 25m) has been degraded to soil moisture resolution (800m x 800m) using a mean filtering algorithm. The soil moisture data retrieved from ESTAR instruments during the SGP97 experiment were collected and used to calibrate and validate the retrieval algorithm. The technical details about the instruments and the methodology used in the field measurement of soil moisture can be found in (Jackson et al. 1999). For the first processing steps, we classified the soil data into three classes based on its water content: class 1 (dry soil 0-10%), class 2 (slightly wet soil 11-20%), and class 3 (wet soil +21%). The vegetation and land-cover data collected during the SGP97 experiment have been used as additional input to the neural networks and fuzzy logic methods.

NEURAL NETWORKS

Artificial neural networks have been applied to a wide range of problems in many disciplines. They have been increasingly used since 1988 for the classification of remotely sensed images (Paola and Schowengerdt, 1995).
multi-layer neural network (or perceptron) was used in this research. The perceptron NN is organized into layers where each node transforms the inputs received from the nodes of the previous layer. The adjacent layers are fully interconnected. The input to one node is the weighted sum of the outputs of the previous layer nodes. This sum is then passed through an activation function to produce the final output. The activation function is usually a sigmoid or hyperbolic tangent, which are non-linear functions that have an asymptotic behavior (Rumelhart et al. 1986).

The training stage consists in adjusting the connection weights (randomly initialized) in order to decrease the difference between the network output and the desired outputs (truth data). The training data were presented to the input layer and propagated through the hidden layer to the output layer. The differences between the computed and the desired outputs were computed and feed backwards to adjust the network connections. This iterative process shown in figure 1, continued until the mean square error reached a preset threshold or the validation criteria were reached. When one of the two criterions is met, the training is stopped and the weight values saved. The trained network may now be used as a classifier.

In general, the complex networks are able to achieve accurate classification of the training pixels compared to simple networks. However, the problem with complex networks is their high risk of overtraining. In the this study, we present the different steps of network architecture optimization, its size and complexity, number of training data, learning algorithm, and training process. The effect of the number of training pixels on the classification process has also been evaluated. Often, the increase of the number of training pixels increases the training time, so it is necessary to find out the optimum size of the training set. Further, the training data must cover the entire distribution for each particular class. After several successive runs of the same network, we have found that, by increasing the number of training pixels, we are able to achieve a slightly higher accuracy on testing pixels. However, once the size of training data reached to maturity, no significant increase in accuracy has been observed.

To optimize the internal configuration of the neural network, the same network was trained 25 times with the same architectural configuration. The results showed that, by using two hidden layers and equal number of nodes in each layer, the standard deviation of the accuracy of 25 runs remains very low. Further, the increase of the number of nodes in each hidden layers does not improve the overall accuracy. The results indicate that the classification accuracy increases when the number of hidden nodes is equal in each of the hidden layers. However, when a single hidden layer was used, the number of nodes should be greater than the number of nodes in the input layer to get reliable results. Concerning the error variability in 25 successive runs, the results are stable when the number of hidden nodes in single layer is less than 22. This showed that, by increasing the number of nodes to more than 6 times the input data, no improvement has been found. Based on above results, the network architecture 3:10:3 and 3:10:1 was used for the next processing steps. The [3:10:3] architecture was used when network trained using three soil moisture classes. However, [3:10:1] architecture was used when network is trained directly by feeding normalized values of soil moisture.

The proper selection of training data and internal parameter is a crucial step in achieving best results. Training samples should adequately represent all classes. In this project, data selected for training (500), validation (200) and testing (300) by random process from total 900 pixels, which are randomly selected from the total image of 3960 pixels (120x33). One output neuron was assigned for each soil moisture class. The training data is used for computing and updating the network weights and the validation data is used for stopping the training by monitoring the validation error during the training process. The testing data is not used during the training process, and is only used to test the neural network performance.

The neural network outputs calculated for various threshold limit values have a great impact on the overall classification. One output neuron was assigned for each ground cover class. For each pixel presented in the input layer, a high value (one) was assigned to the neuron that does correspond to the pixel’s assigned class and a low value (zero) was assigned to the remaining neurons. However, during the classification, a continuous range from the low value to the high value will be computed for each output neuron. To avoid that the network forces the classification of all pixels, we have introduced a threshold (value between 0 and 1) to decide if a class will be assigned to the input pixel or if this pixel will be considered as unclassified. Thus, a pixel is considered unclassified if all output values are lower than this threshold; otherwise the pixel is assigned the class corresponding to the neuron with the highest value (Ghedira et al. 2004).

The optimal threshold value cannot be identified with certainty without measuring its effect on the overall accuracy of the neural network classification. In this project, the threshold value has been varied from 0.4 to 0.7. The threshold tests have shown that the increase of the threshold value affects the overall classification significantly, as shown in figure 1. Furthermore, the increase of the threshold decision value above 0.4 results in a simultaneous decrease of the percentage of incorrect and correct classified pixels and an increase in the percentage of unclassified pixels. Thus, the increase in threshold limit leads to more nil pixels in soil moisture classification, but increases the confidence that the classified pixels have been correctly classified.
One of the major concerns in the process of neural network training is the over-training. The neural network’s generalization ability is then compromised and the classification space becomes narrowly defined around the training pixels. Normally, as it is the case for the learning set error, the error computed on the validation set decreases during the initial phase of training. However, when the network begins to overfit the learning data, the error on the validation set will begin to increase slowly for the next iterations, shown in figure 2. At this time, the training process must be stopped, and the neural network weights corresponding to the minimum validation error must be identified and maintained for the next steps (Ghedira and Bernier, 2004).

Figure 2. Effect of threshold limit in classifying pixel.

Figure 2. Role of each training data set in the training process (Ghedira and Bernier, 2004).
FUZZY LOGIC METHOD

The fuzzy set theory is a mathematical tool designed to deal with imprecise and vague data. In the classical logic, an element is expressed as in binary terms: 0 or 1, yes or no, black and white; in terms of Boolean algebra. A fuzzy set generalized the Boolean set, by allowing partial membership in a set, values ranges from 0 to 1. The fuzzy logic (FL) technique based on fuzzy set theory has been applied in many areas where relationship between variable is not empirically defined. The elements of a fuzzy set have different degree of membership values. The membership value ranges between 0 and 1 depends upon partial or full membership.

A mathematical function defines the degree of an element's membership in a fuzzy set is called membership function. The fuzzy logic has been used in very wide the areas of applications: process control, management and decision making, operations research, economics and engineering. The advantage of fuzzy logic is in dealing with uncertainty and imprecision in a decision-making process, and thus offers a new approach for classifying remotely sensed images (Nedeljkovic, 2004).

A subtractive clustering technique (Fuzzy Logic Method) was used to predict the soil moisture from SAR images and compared to NN systems output. The genfis2 algorithm provided by MATLAB® software use a subtractive clustering method to generate Fuzzy Inference System (FIS). The genfis2 function uses the subclust function to estimate antecedent membership function and set of rule. Further, subclust function uses linear least square method to determine each rule’s consequent equation, and returns FIS structure that contains a set of fuzzy rules. The subclust function assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points (MATLAB Toolbox, 2004).

The first cluster center having highest potential was selected from data points. The data points under the radii of cluster center have been marked. To find out next cluster, all the point from the radii of first cluster have been removed and looked for data point having highest potential to become next cluster center. This process will iterated until all the data is within a radii of cluster center. The radii used for marking is a value varied between zero and one. The small radii values generally results in finding a few large clusters. In this study, the technique were run for various radii values and observed that the optimum radius is about 0.55, which is used for further analysis of soil moisture estimation.

![Image](image.png)

Figure 3. Comparison between neural network and fuzzy logic output.

RESULTS AND DISCUSSION

The spatial and temporal information of soil moisture is an important parameter in land use management. Active and passive microwave remote sensing have shown capabilities in estimating the soil moisture in faster and reliable ways. The soil moisture and backscattering coefficient relationship is mainly due to the dielectric properties of soil and water. The relationship is influenced by various surface and sensor characteristics. This influence of
various parameters can be better understood by techniques like neural network and fuzzy logic, where more than one input parameter can be used to improve the relationship.

The neural network and fuzzy logic techniques have been tested in this project to retrieve soil moisture from backscattering data. The figure 3 show the output calculated by neural network and fuzzy logic for the same training and testing data set. By comparing these two figures, we observed that, neural network overestimate the soil moisture for the small soil moisture values (less than 10%) and underestimate when soil moisture is greater than 20%. The fuzzy logic estimation of soil moisture is more balanced, although the overall accuracy is approximately the same.

Through several successive runs of both techniques, we observed that, the neural network model shows higher potential to estimate soil moisture. However, we have noted a high variation in accuracy for successive runs of the NN model. Using the same inputs, the fuzzy logic outputs have very low variation in accuracy. Although, the prediction made by neural network is higher than fuzzy logic in several runs of the model, but we found that the prediction made by fuzzy logic is more stable in nature.

ACKNOWLEDGEMENT

This research was funded by the NOAA Cooperative Remote Sensing Science & Technology Center (NOAA-CREST) and the City University of New York.

REFERENCES


