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Classification of ASAS Multiangle and Multispectral Measurements Using Artificial Neural Networks

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Because the anisotropy of the Earth's surface reflectance is strongly influenced by vegetation cover, multidirectional remotely sensed data can be highly effective in discriminating among land cover classes. This article explores the use of multiangle and multispectral data from the Advanced Solid-State Array Spectroradiometer (ASAS) in land cover mapping using artificial neural networks. A multilayer feed-forward neural network is trained to identify five land cover classes in Voyageurs National Park, Minnesota. Multiangle data achieve 89% of accuracy when applied to a single band (774–790 nm), 7-directional imagery and 88% accuracy when applied to multispectral nadir data. Analysis of error using the confusion matrix indicates that the higher classification accuracy is obtained primarily for three classes: deciduous forest, wetlands, and water. The results suggest that 1) directional radiance measurements contain much useful information for discrimination among land cover classes, 2) the incorporation of more than one spectral multiangle band improves the overall classification accuracy compared to a single multiangle band, and 3) neural networks can successfully learn class discriminations from directional radiance data and/or multidomain data.

INTRODUCTION

Conventional multispectral classification is the process of discretizing spectral digital image data (e.g., satellite or aircraft multispectral imagery) into classes of known identity. Traditionally, parametric methods based on simple statistical models have been used in the classification of these data. For example, maximum likelihood measure is based on the Gaussian model for the distribution of pixels from each class. These techniques yield classification accuracies of around 60–90%, with the lower values encountered in the contexts where complicated data sets are used and/or when large number of classes have to be identified. To overcome these limitations, new and alternative models, including artificial neural networks, have been introduced. Recently, Landsat Thematic Mapper (TM) data have been classified using feed-forward neural networks by Kiang (1992), Hepner et al. (1990), McClellan et al. (1989), Civco (1993), and Howald (1989). There have also been attempts to use other remotely sensed data including Landsat Multispectral Scanner (MSS) Lee et al., 1990), the Synthetic Aperture Radar (SAR) terrain image data (Decatur, 1989) and Systeme Pour l'Observation de la Terre (SPOT) (Dreyer, 1993). These applications have proved successful and generally result in greater classification accuracies compared with the conventional techniques.

More sophisticated approaches using neural networks involve an integration of data sets, that is, multidomain data; for example, Key et al. (1989) use the Advanced Very High Resolution Radiometer (AVHRR) data in conjunction with the Scanning Multichannel Microwave Radiometer (SMMR) for the classification of four surface and eight cloud classes in the Arctic. Benediktsson et al. (1990) combine remotely sensed data with ancillary topographic information. Multitemporal data have been used by Kanellopoulos et al. (1990). Most of these studies have used feed-forward networks

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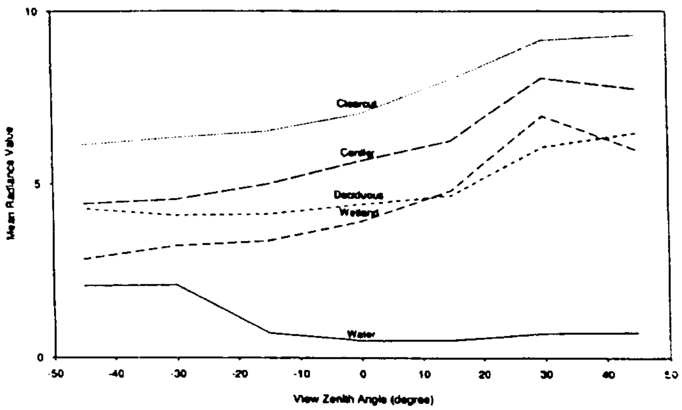

Figure 1. Mean radiance values (mW cm^{-2} sr^{-1} μm^{-1}) for five land cover classes as a function of viewing angle of ASAS Band 24 (769–795 nm); solar zenith angle is 34°.

trained using the backpropagation algorithm. More recent approaches have utilized neural network architectures other than backpropagation. For example, Salu and Tilton (1993) introduce an unsupervised multilayer feed-forward classifier called "binary diamond" for the classification of multispectral data. Gopal et al. (1994) use a supervised model called FuzzyART (Carpenter et al., 1991) in the classification of normalized difference vegetation index (NDVI) data obtained from AVHRR images for the Sahel. These works suggest that neural networks provide a viable alternative for classifying remotely sensed data.

A relatively unexplored domain in remote sensing is the use of directional radiance measurements in classification. So far, very little attention has been paid to this domain compared to the spectral domain (Kimes et al., 1991). However, several new sensors proposed for the Earth Observation System (EOS) will offer information about the directional as well as the spectral variations of the reflected radiance. These sensors include the Moderate Resolution Imaging Spectrometer (MODIS) and the Multiangle Imaging Spectroradiometer (MISR), which are planned for launch in 1998 on the EOS-AM1 platform.

The directional anisotropy of the radiance reflected from terrestrial surfaces can be used as an index to discriminate among land cover classes, Figure 1 shows the mean radiance values (in mW cm^{-2} sr^{-1} μm^{-1}) for representative sample of five land cover classes—conifer, water, deciduous, clearcuts, and wetlands—as measured by the Advanced Solid-state Array Spectroradiometer (ASAS) (Irons et al., 1991) in the principal plane of the sun, as a function of viewing angles. The patterns of directional response are generally similar for the four vegetated covers, although they differ in specific features. Water is clearly separable from the others.

A primary objective of this research is to demonstrate the feasibility of using directional radiance information in land cover classification. The effects of multidirectional data, multispectral data, and multidomain (multidirectional and multispectral) data on classification accuracy are discussed. A second objective is to introduce artificial neural networks to approximate the input–output relationship between directional remotely sensed data and land cover class memberships.

ASAS IMAGERY

The Advanced Solid-state Array Spectroradiometer (ASAS) is a pointable aircraft-borne spectroradiometer with a unique capability to collect high spectral resolution data in the visible and near-infrared region of the spectrum at multiple directions (Irons et al., 1991). Prior to September 1992, the ASAS focal plane held a charge-injection-device (CID) area detector array providing 29 spectral bands from 451 nm to 871 nm with an approximately 15 nm bandwidth. In 1992 the CID detector array was replaced with a charge-coupled-device (CCD) array providing 62 visible and near-infrared spectral bands with a spectral resolution of approximately 11 nm.

Imagery from ASAS has a pixel size determined in the across-track direction by platform altitude, and in the along-track direction by the electronic readout rate and its 25° field of view. For the conditions of our acquisition, nadir pixel size was 2.5 m by 4.0 m. Images are acquired from multiple fore-to-aft view directions (45° forward to −45° aft in 15° increments in the case analyzed here) as the aircraft approaches and recedes from the target. The ASAS instrument is operated by the NASA / Goddard Space Flight Center, Laboratory of Terrestrial Physics and flown on NASA's C-130 aircraft.

ASAS data were received in a format of two header records followed by 30 bands recorded in a band-sequential format. The original 16 bit data were compressed to 8 bits as needed for image display and as inputs to the network. Figure 2 displays Band 24 (774–790 nm) showing the scene under investigation.

A 400 by 244 pixel image of Voyageurs National Park was chosen for the study. The scene consists of five distinctive land cover classes—water (lake), conifers, deciduous forest, wetlands, and a clearcut. The seven look angle images were registered to each other prior to any processing. Training and testing data sets were extracted from the image. The training data consisted of 1623 pixel for each class, and the test data consisted of 100 randomly chosen pixels per each class. The near-infrared ASAS Band 24 was used because, in this wavelength range, atmospheric effects are minimal.

ASAS data suffer from geometric distortions due to the off-nadir viewing angles and to aircraft motion during data acquisition. The distortion results in image

Figure 2. ASAS Band 24 of Voyageurs National Park, Minnesota, on 26 June 1988 with a solar zenith angle of 34°.

misregistration between look angles. The development and application of the neural network required image-to-image registration to ensure that each pixel from the seven view angles exactly represent the same location on the ground. A simple rubber sheet wrapping technique was adopted to register all the off-nadir view images to the nadir image, that is, the base image. Second- and third-order polynomials were fitted to sets of control points that were identified in the images to achieve registration. Reasonable root-mean-square errors were achieved in most cases. In future studies we plan to follow a more rigorous technique of directional images registration such as the one developed by Allison et al. (1994).

CLASSIFICATION OF ASAS MULTIANGLE DATA

Neural Network Modeling

In this article we use feed-forward neural networks, which have influenced the development in the field of neural networks during the past decade. The problem

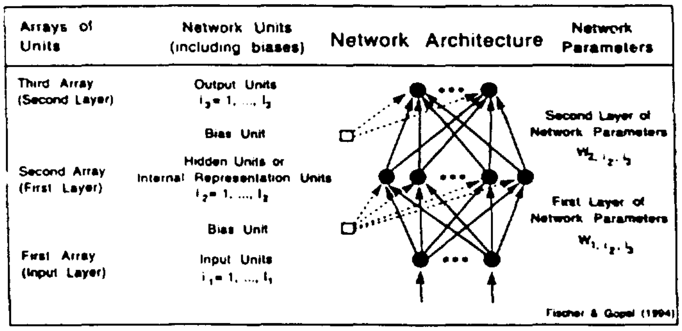

Figure 3. The general two-layer neural network model.

addressed by such networks is the approximate implementation of an input–output relation by means of supervised training. We consider two-layer feed-forward networks with one (or more) hidden layers (Fig. 3), which is the leading case of feed-forward neural networks. A detailed discussion and review of the multilayer feed-forward networks and the algorithm used for training called "backpropagation" is given in Rumelhart et al. (1986a,b).

Fischer and Gopal (1994) view the application of neural network modeling as a three-stage process. The first stage, *model identification*, involves determining the number of input, output, and hidden units. The choice of the number of hidden units is not an easy task. It is generally dictated by the problem and involves considerable judgement on the part of the experimenter. The intuitive rule of "the more the better" might be used, since the number of hidden units controls the model's flexibility. On the other hand, networks with large hidden units may become counterproductive as they introduce many degrees of freedom and may not lead to optimal predictions. Weigend et al. (1991) suggests that the number of weights should be less than 1 / 10 of the number of training patterns.

The second stage, called *model estimation*, refers to choice of a reasonable network training strategy by which various parameters including choice of error function, training by pattern or epoch, sequential or random ordering of training vectors, the iterative procedure, appropriate initial conditions, network parameters, and the weight updates. The final stage is called *model testing or prediction*, where the prediction quality of the network is assessed using performance measures like root mean square error (RMS), R^2, and error matrix (Congalton, 1991).

Model Identification Stage

The neural network designed for the experiment consisted of four fully connected layers. The input layer consisted of seven processing units or nodes representing the seven view angles for a pixel as captured by ASAS. Each input brightness value was scaled between

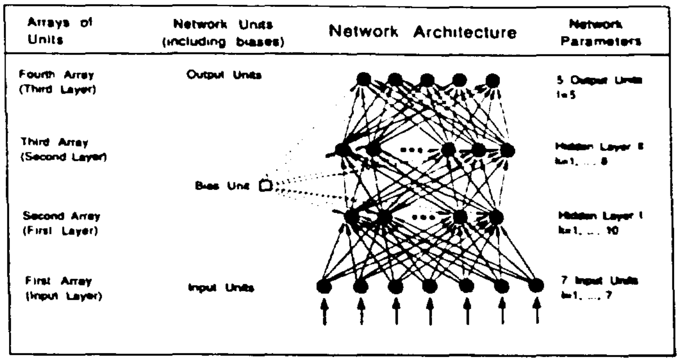

Figure 4. The neural network architecture used in the classification of the ASAS data.

− 1 and 1. The number of hidden units was determined through experimental simulations. The first hidden layer comprised 10 processing units and the second 8 units. The output layer had five nodes, each representing one of the five classes to be classified. The output of the neural network, was represented using a coding scheme in which the output vector consisted of five elements representing the five land cover classes of interest. For example, if a pixel belongs to class 3, the output from node 3 in the output layer was set to a value of 1 and the remaining outputs from the other nodes were set to 0. Thus the target output vector representing class 3 would be (0,0,1,0,0). The architecture of the network is shown in Figure 4. The initial parameters were drawn from a uniform distribution. Five different random initializations were used to analyze variations due to random initial conditions.

A hyperbolic tangent transfer function was used to calculate the activation of the nodes. A learning rate of 0.3 and a momentum rate of 0.4 were used. Training was stopped when the root mean square error was less than 0.01. Table 1 shows the results of the five simulations, the number of epochs (one epoch represents the presentation of eight training samples to the network) required to reach convergence. Each simulation presents a different set of initial weights, and thus

Table 1. Performance of 7:10:8:5 Model during Training in Terms of CPU time and Number of Epochs (a Learning Rate of 0.3 and a Momentum Rate of 0.4)

Simulation Number	*Training*	
	Epochs	*CPU Time*
1	25,480	3:49
2	35,280	5:17
3	49,504	7:25
4	39,008	5:51
5	50,024	7:30
Mean	39,859.2	5:58
Std. Dev.	10,305.34	1:32

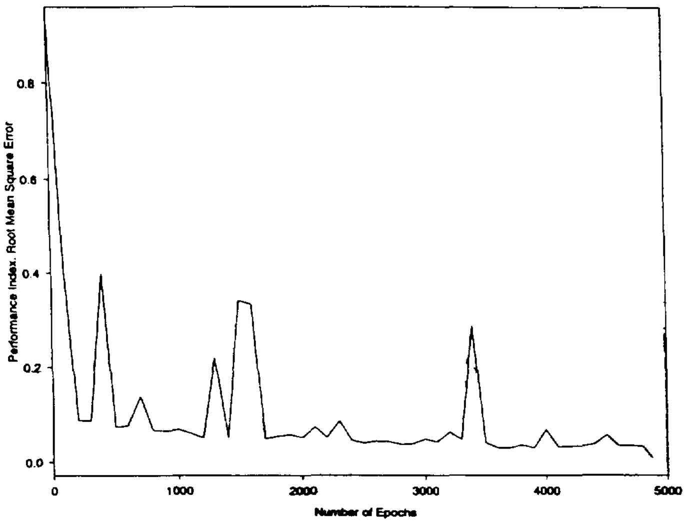

Figure 5. Training performance of the (7:10:8:5) neural network model in terms of the root mean square error.

Table 1 shows the variations in performance due to initial conditions. Best performance is obtained using Simulation 4 in Table 1, which is closer to the mean (of the five simulations) and has much less variance. Simulations 1 and 2 reached convergence earlier (less CPU time) but are not similar to the mean. Hence we selected Simulation 4 for the testing phase and for our discussion pertaining to classification using a neural network.

Model Estimation and the Overfitting Problem

Whereas the stage of identification was concerned with identifying an appropriate model, the stage of parameter estimation is devoted to determination of the magnitude and the sign of the parameters of the (7:10:8:5) network model. Figure 5 shows the evolution of training accuracy in terms of the performance measure, that is, root mean square error, plotted against the number of epochs (each epoch represent eight iterations). The network's root mean square first decreased rapidly (until 1800 epochs), and then fluctuated (until 15,000 epochs), before exhibiting a more steady pattern (around 25,000 epochs). It took nearly 39,000 epochs for the network to reach the predefined criteria of convergence.

A serious problem at this stage is the overfitting problem which leads to poor generalization. This arises when the neural mapping function tries to fit all of the fine details in the training data set, rather than capturing the underlying trends in the data (Bishop, 1991). It is thus necessary to rectify the mapping function and hence improve the generalization capability of the neural model. We used a simple technique called "pruning" (Samad, 1989) in order to reduce the size of the network and thus the size of the mapping function, which, in turn, reduces the computational complexity. This process involves monitoring the weights of the connections of the network in the training phase. A weight threshold of ± 0.8 was used. Using this procedure, those connections weights that did not grow more than the prespecified threshold were "pruned," and the reduced network (with the pruned connections) was retrained once more. We found 17 connections that could be pruned in the (7:10:8:5) network, and the pruned network only reused 25,280 epochs to reach the convergence criteria. Note that this procedure is a heuristic measure. Better approaches exist that systematically eliminate weights and remove hidden units, including the weight elimination method using a complex cost function (Chauvin, 1990; LeCun et al., 1990) and the validation method of Weigend et al. (1991). Our future research efforts will involve exploring these methods to address the overfitting problem, which is a serious issue using real world data.

Table 2. Prediction Performance of 7:10:8:5 Model in Terms of R^2 for Different Classes

Class	R^2
Water	0.916
Deciduous	0.945
Wetlands	0.898
Conifer	0.997
Clearcut	0.953

Model Testing or Prediction Stage

So far, we have concentrated on describing the training behavior of the network. This stage involves the assessment of a network prediction ability with novel data. That is, the ultimate task of learning is to generalize outside the training set and predict outputs for unseen input pixels. Table 2 reports the prediction performance of the (7:10:8:5) neural network on the testing data set in terms of R^2 between the target class and the corresponding neural prediction. As can be seen, R^2 values of more than 0.9 are obtained for conifer forest, clearcuts, deciduous forest, and water, while wetlands shows a slightly lesser R^2.

Table 3 shows the confusion matrix for the classified test data using ASAS band 24 multiangle data. The total accuracy is 97.4%, and the errors of omission are 13 out of 500. There is some confusion between water and wetlands, and deciduous forest and clearcuts. These errors might reflect misregistration errors that occur at the boundaries between classes. In general, the neural network appears to be a very effective classifier.

CLASSIFICATION OF ASAS MULTISPECTRAL DATA

An interesting issue in this analysis of directional data versus multispectral data is to assess the classification

Table 3. Confusion Matrix for the Neural Network Classifier

Ground Truth	Landcover Class Using Neural Network Classifier				
	Lake	Deciduous	Wetland	Conifer	Clearcuts
Water	92	0	8	0	0
Deciduous	0	95	0	0	5
Wetland	0	0	100	0	0
Conifer	0	0	0	100	0
Clearcut	0	0	0	0	100

accuracy in each case. A comparison of single-band multidirectional data versus six-band multispectral data was undertaken in this study. An image database consisting of six nadir ASAS spectral bands for Voyageurs National Park were used. This database consists of ASAS Band 2 (458–472 nm), ASAS Band 6 (513–528 nm), ASAS Band 8 (541–556 nm), ASAS Band 15 (641–656 nm), ASAS Band 21 (730–746 nm), and ASAS Band 24 (774–790 nm).

A neural network was developed to perform the classification. The input layer consists of six nodes, each node representing one of the six spectral bands, and the output layer of five nodes each representing one of the five land cover classes. A similar architecture of 10 hidden nodes in the first hidden layer, and eight nodes in the second hidden layer was used. The image was classified using the trained network, and the classification accuracy results are shown in Table 4.

DISCUSSION

The following discussion pertains to the classification of the entire image. Figure 6 shows the classified image of the scene when using ASAS multiangle data only. Note that the classified image (Fig. 6) visually looks similar to the original image shown in Figure 2. The effects of misregistration are clearly seen along the boundaries that separate some classes, for example, the boundary between lake and wetlands, where pixels are labeled as conifers. Similarly the boundary between lake and deciduous forest shows the effects of misregistration. The impact of misregistration is a serious issue that warrants future research.

Table 4 compares the results of classifying the whole image using ASAS multiangle data and ASAS multispectral data, each separately. The area weighted accuracy for the multidirectional classification is 89%, and for the nadir multispectral classification data are 88%. There is no significant difference between the two classification accuracies. The results demonstrate that multidirectional data is as useful as multispectral data for land cover classification. The multiangle classification in Table 4 overestimates the water class (1%), and the deciduous class (less than 1%). The multispectral classification largely overestimates the deciduous class and underestimates the wetlands area. Both classifications approximately equally underestimate the conifer class, and overestimate the clearcut areas.

An interesting issue in the use of multidirectional ASAS data is the effect of increasing the number of spectral bands on the classification accuracies. A comparison of multidirectional data and multidomain data (a combination of multispectral and multidirectional) was undertaken in another study (Abuelgasim and Gopal, 1994). A scene consisting of 400 by 303 pixels of Voyageurs National Park was classified with ASAS Band 10 (570–585 nm). ASAS Band 15 (642–656 nm), and ASAS Band 24 (774–790 nm).

In this study, the effect of each of the three ASAS bands on classification was first assessed independently. In each case, the same neural network architecture was used. Second, the effect of combinations of ASAS Bands 10 and 15 and ASAS bands 15 and 24 on classification was analyzed. The input layer of the ANN architecture was expanded to reflect the changes in the size of the input vector. Other layers in the network remained the same. The overall classification results are shown in Table 5.

In terms of multidirectional data alone, the near-infrared ASAS Band 24 produced the best classification

Table 4. Classification Accuracy for Land Cover Classes Using Multiangle and Multispectral Data

Land Cover Class	*Ground Cover (# of Pixels)*	*Ground Cover (% Cover)*	*Multiangle Data (# of Pixels)*	*Multiangle Data (% Cover)*	*Multispectral Data (# of Pixels)*	*Multispectral Data (% Cover)*
Water	8,640	8.85%	9,690	9.93%	8,781	9.00%
Deciduous	17,200	17.62%	17,718	18.15%	18,978	19.44%
Wetlands	16,808	17.22%	14,781	15.14%	14,468	14.82%
Conifer	47,776	48.95%	44,414	45.51%	44,395	45.49%
Clearcut	7,176	7.35%	10,997	11.27%	10,978	11.25%
Accuracy				89%		88%

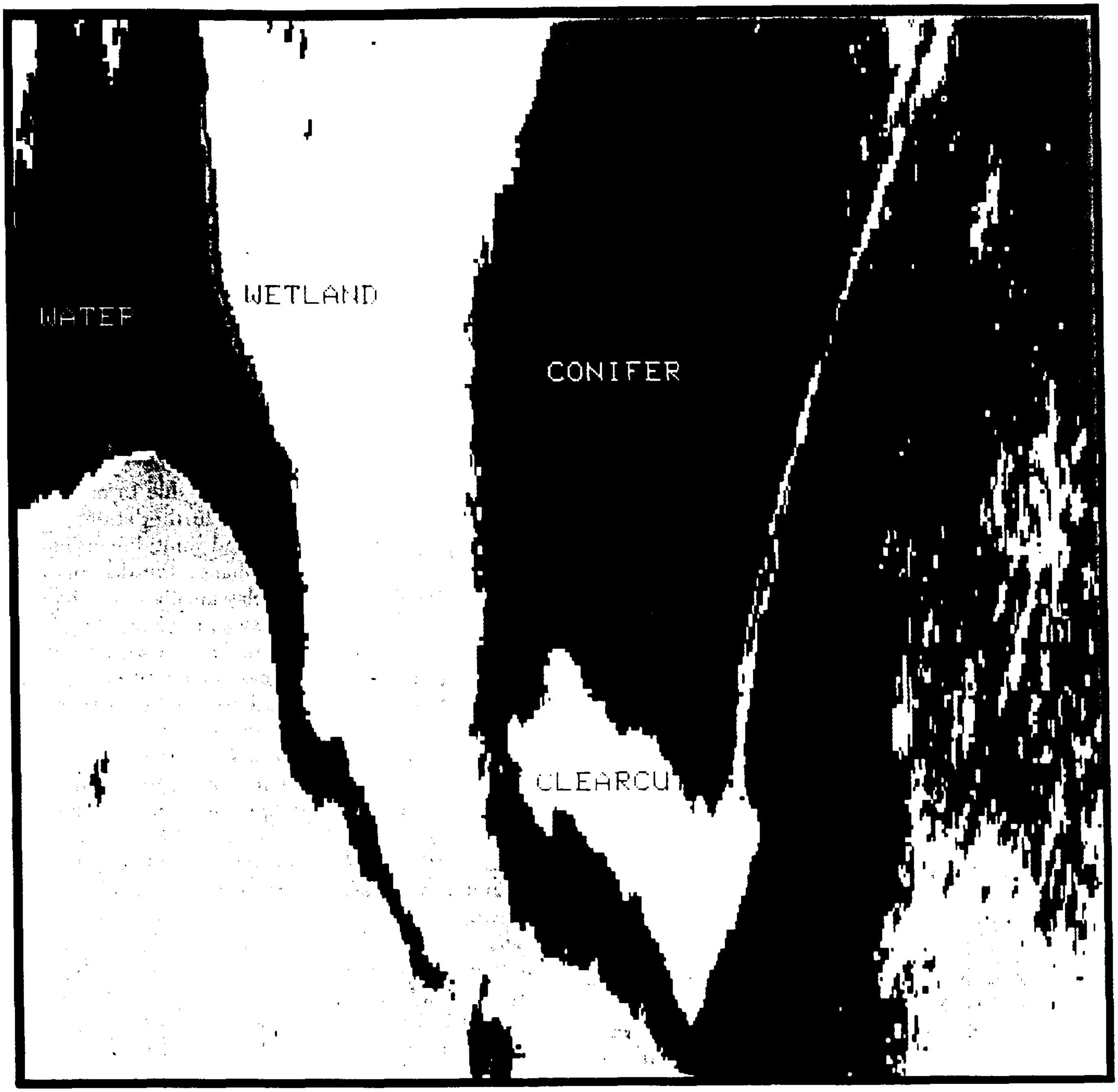

Figure 6. Classified image of Voyageurs National Park using neural network classification. Blue represents water, orange represents deciduous, yellow represents wetlands, red represent conifer, and white represent clearcut areas.

result (85%), compared with ASAS Band 10 (64%) and ASAS Band 15 (61%). An improvement in accuracy is noted using the multidomain data sets. A combination of ASAS Bands 10 and 15 increases the accuracy to 65% representing an improvement of nearly 7% and 2% over using ASAS Bands 15 and 10 individually. Similarly, there are gains in accuracy using the combination of ASAS Band 15 and 24; total accuracy increases to 87% representing a substantial improvement of 43% in the case of ASAS Band 15 and a modest increase of 2% over using ASAS Band 24 alone.

This finding is not surprising. Multidirectional data by itself tend to have lower intrinsic dimensionality; but, in the case of multispectral and multidirectional data, more discriminative information is available, and an improvement in classification should be expected. However, in general, the improvement was not dramatic in this study. One possible reason may be the fact that the scene under investigation was simple; it has only five land cover classes, and one spectral band with multiangle views may be sufficient to achieve reasonable accuracy. Though this might be a limitation, as it does

Table 5. Classification Accuracy for Land Cover Classes Using Multiangle and Multispectral ASAS Data

Spectral Band	*Classification Accuracy*
ASAS Band 10	64%
ASAS Band 15	61%
ASAS Band 24	85%
ASAS Bands 10 and 15	65%
ASAS Bands 15 and 24	86%

not exploit the power of multiangle data, our future plans are to seek more sophisticated multiangle and multispectral data sets, with more complex classes to fully analyze the potentials of multiangle and multidomain data for land cover classification.

CONCLUSIONS

This study demonstrates that directional radiance measurements can be used to effectively discriminate among land cover classes. This approach is useful in areas where land surface classes cannot be discriminated based solely on their spectral signature. The directional reflectance pattern exhibited by various classes is particular to each class and is dependent on important elements such as size, shape, and spatial distribution of the constituent elements of each cover type.

The study also demonstrated that the incorporation of more than one directional band (multidomain data) enhances the classifier's ability in discriminating among land cover classes. Future analysis of landscape patterns will likely incorporate more sophisticated information and data from a variety of sources and domains, that is, multitemporal, multidirectional, multispectral. The automatic production of up-to-date land cover maps from satellite imagery requires optimal classification and spatial generalization procedures. New developments in the field of satellite sensor systems, including the launch of more satellites with synthetic aperture radar systems, new visible and infrared band sensors with improved ground resolution, and launch of polar platforms carrying medium resolution imaging spectrometer systems and multilook angle sensors, etc., will result not just in a tremendous quantity of image data, but data from many different spectral channels and from diverse parts of the electromagnetic spectrum. Conventional pattern classification approaches often do not provide high levels of accuracy for these types of data. Such complex data may require more sophisticated classification and post-classification refinement techniques. Neural network architectures may be more reliable tools for extracting information from the detailed spectral measurements and radar backscatter signals.

The use of neural networks in remote sensing is relatively new. Artificial neural networks have a significant role to play in this context since they can handle massive, complex, and incomplete data sets efficiently and result in greater classification accuracies. In addition, neural networks are distribution-free and offer a further advantage over most statistical methods, where a knowledge of the distribution function is necessary and data are assumed to be Gaussian.

This article introduces a class of neural network models called feed-forward neural networks that implement a functional input–output relationship expressed in a general, modifiable form. Learning is accomplished by means of the backpropagation algorithm that functionally modifies the adaptive setting of weights. The main results obtained in the study demonstrate that the neural network we constructed successfully learns the input–output mapping between the directional radiance measurements and the land cover class. There are some errors in classification especially at the boundaries of certain classes. This may be partly due to misregistration, an issue that warrants some further attention. The combination of multispectral and multidimensional information for classification enhance the discriminative power and lead to improved classification, with complex scenes especially if more classes are to be identified.

There are some fundamental problems in the neural network approach that deserve further attention. First, supervised learning using backpropagation can be stuck in a local minimum of the error function due to the gradient-based learning rules. These can be viewed as potential pitfalls undermining this type of supervised learning. Second, the backpropagation procedure requires a large number of computations per iteration. The algorithm tends to run slowly unless implemented in parallel hardware. Third, overtraining of the feed-forward network may lead to overgeneralization and fitting of noise by the network. Obviously despite these limitations, these neural networks offer many advantages over conventional approaches. Our future research in this area will explore different types of neural network architectures in the classification of multidirectional and multispectral data sets.

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REFERENCES

Abuelgasim, A. A., and Gopal, S. (1994), A hybrid neural network model for classification of multiangle and multispectral ASAS radiance measurements, *in* Proc. IGARSS Symp., Pasadena, CA, Vol. 3, pp. 1670–1675.

Allison, D., Barnsley, M. J., Lewis, P., Dyble, N., and Mulle, J. (1994), Precise geometric registration of ASAS airborne data for land surface BRDF studies, in *Proc. IGARSS Symp.*, Pasadena, CA, Vol. 3, pp. 1655–1657.

Benediktsson, J. A., Swain, P. H., and Ersoy, O. K. (1990), Neural network approaches versus statistical methods in classification of multisource remote sensing data, *IEEE Trans. Geosci. Remote Sens.* 28(4):540–552.

Bishop, C. (1991), Improving the generalization properties of radial basis function neural networks, *Neural Comput.* 3: 930–945.

Carpenter, G. A., Grossberg, S., and Rosen, D. B. (1991), FuzzyART: fast stable learning and categorization of analog patterns by an adaptive resonance system, *Neural Networks* 4:759–771.

Chauvin, Y. (1990), Generalization performance of overtrained networks, in *Neural Networks, Proc. EURASIP Workshop*, (L. B. Almeida and C. J. Wellekins, Eds.), Portugal, Springer-Verlag, New York, pp. 46–51.

Civco, D. L. (1993), Artificial neural networks for land cover classification and mapping, *Int. J. Geog. Info. Sys.* 7:173–186.

Congalton, R. (1991), A review of assessing the accuracy of classifications of remotely sensed data, *Remote Sens. Environ.* 37:35–46.

Decatur, S. E. (1989), Application of neural networks to terrain classification, *Proc. Int. Joint Conf. Neural Networks*, 1:283–288.

Dreyer, P. (1993), Classification of land cover using optimized neural networks on SPOT data, *Photogramm. Eng. Remote Sens.* 5:617–621.

Fischer, M. M., and Gopal, S. (1994), Comparative performance comparisons between multilayer feed-forward networks and the conventional spatial interaction model, *J. Reg. Sci.* 34(4):503–527.

Gopal, S., Sklarew, D. M., and Lambin, E. (1994), Fuzzy-neural networks in multitemporal classification of land cover change in the Sahel, in *Proc. DOSES Workshop on New Tools for Spatial Analysis*, Lisbon, Portugal, DOSES, EUROSTAT, ECSC-EC-EAEC, Brussels, Luxembourg, pp. 55–68.

Hepner, G. F., Logan, T., Ritter, N., and Bryant, N. (1990), ANN classification using a minimal training set: comparison to conventional supervised classification, *Photogramm. Eng. Remote Sens.* 56(4):469–473.

Howald, K. J. (1989), Neural network image classification, in *Proc. 1989 ASPRS-ACSM Fall Convention*, American Society of Photogrammetry and Remote Sensing, Falls Church, pp. 207–215.

Irons, J. R., Ranson, K. J., Williams, D. L., Irish, R. R., and Huegel, F. G. (1991), An off-nadir pointing imaging spectroradiometer for terrestrial ecosystem studies, *IEEE Trans. Geosci. Remote Sens.* 29:66–74.

Kanellopoulos, I., Varfis, A., Wilkinson, G. G., and Megier, J. (1990), Land-cover discrimination in SPOT HRV imagery using an artificial neural network a 20-class experiment, *Int. J. Remote Sens.* 13(5):917–924.

Key, J., Maslanik, J. A., and Schweiger, A. J. (1989), Classification of merged AVHRR and SMMR Arctic data with neural networks, *Photogramm. Eng. Remote Sens.* 55(9):1331–1338.

Kiang, R. K. (1992), Classification of remotely sensed data using OCR-inspired neural network techniques, in *Proc. IGARSS Symp.*, Houston, TX, Vol. 2, pp. 1081–1084.

Kimes, D. S., Harrison, P. R., and Harrison, P. A. (1991), Learning class descriptions from a data base of spectral reflectance with multiple view angles, *IEEE Trans. Geosci. Remote Sens.* 30:315–325.

LeCun, Y., Denker, J. S., and Solla, S. A. (1990), Optimal brain damage, in *Advances in Neural Information Processing Systems 2 (NIPS 89)* (D. S. Touretzky, Eds.), Morgan Kaufmann, San Mateo, CA, pp. 589–594.

Lee, J. S., Weger, W. C., Sengupta, S. K., and Welch, R. M. (1990), A neural network approach to cloud classification, *IEEE Trans. Geosci. Remote Sens.* 28:846–855.

McClellan, G. E., DeWitt, R. N., Hemmer, T. H., Mattheson, L. N., and Moe, G. O. (1989), Multispectral image processing with a three layer backpropagation network, *Proc. Int. Joint Conf. Neural Networks* 1:151–153.

Rumelhart, D. E., Hinton, G. E., and Williams, P. J. (1986a), Learning representations by back-propagating errors, *Nature* 323:533–536.

Rumelhart, D. E., Hinton, G. E, and Williams, R. J. (1986b), Learning internal representations by error propagation, in *Parallel Distributed Processing. Exploration in the Microstructure of Cognition. Volume 1: Foundations* (D. E. Rumelhart, J. L. McClellan, and the PDP Research Group, Eds.), The MIT Press, Cambridge, MA, Vol. 1, pp. 318–362.

Salu, Y., and Tilton, J. (1993), Classification of multispectral image data by the binary neural network and by nonparametric, pixel-by-pixel methods, *IEEE Trans. Geosci. Remote Sens.* 31(3):606–617.

Samad, T. (1989), Backpropagation extensions, Honeywell SSDC Technical Report, Golden Valley, MN.

Weigend, A. S., Rumelhart, D. E., and Huberman, B. A. (1991), Backpropagation, weight elimination and time series prediction, in *Connectionist Models, Proc. of the 1990 Summer School* (D. S. Touretzky, J. L. Elman, T. J. Sejnowski, and G. E. Hinton, Eds.), Morgan Kaufman, San Mateo, CA, pp. 105–116.

Wharton, S. W. (1989), Knowledge-based spectral classification of remotely sensed data, *IEEE Trans. Geosci. Remote Sens.* 25(3):272–282.