Conifer Species Recognition: An Exploratory Analysis of *In Situ* Hyperspectral Data

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In situ hyperspectral data measured above sunlit and shaded sides of canopies using a high spectral resolution radiometer were analyzed for identification of six conifer tree species. An artificial neural network algorithm was assessed for the identification purpose. Linear discriminant analysis was compared with the neural network algorithm. The hyperspectral data were further processed to smoothed reflectances and first derivative spectra and were separately used in tree species identification. Tree species recognition with data collected from six study sites was tested in seven experiments. The average accuracy of species recognition was obtained at every site. The overall performance of the neural network algorithm was better than that of linear discriminant analysis for species recognition when the same number of training samples and test samples were used. The discriminant analysis produced better accuracy than neural network at one site where many samples (10) were taken from six individual trees. Use of the average spectra of all samples for a particular tree species in training may not result in higher accuracy than use of individual spectral samples in training. Use of sunlit samples alone resulted in an overall accuracy of greater than 91%. The effects of site background including illuminating conditions on tree species spectra were large. Neural networks are sensitive to subtle spectral details and can be trained to separate samples from the same species at different sites. Our experiments indicate that the discriminating power of visible bands is stronger than that of near-infrared bands. Higher recognition accuracies can be obtained in the blue to green or the red-edge spectral region as compared with four other spectral regions. A smaller set of selected bands can generate more accurate identification than all spectral bands.

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Received 21 January 1997; revised 31 May 1997.

INTRODUCTION

In natural resource management, environmental protection, biodiversity and wildlife studies, correct recognition of forest species is important. Conventionally reliable methods for tree species recognition depend mainly on costly, time-consuming, and labor-intensive inventory in the field or on interpretation of large-scale aerial photographs. The use of these methods is frequently limited by cost and time and is not applicable to large areas. Digital remote sensing has been used to identify forest species of large areas, but two problems are encountered: Different tree species often have similar spectral characteristics partly due to the lack of high spectral resolution and large number of spectral bands; and the same tree species may have distinct spectral properties due to illumination conditions on which optical remote sensing is based.

Hyperspectral data in hundreds of spectral bands with very high spectral resolution have been applied to leaf area index estimation (Gong et al., 1995; 1992), biochemistry constituents (Curran, 1989; Card et al., 1988; Johnson et al., 1994; Matson et al., 1994), and decomposition of spectrally mixed pixels (Gong et al., 1994; Boardman, 1989). Although such data allow subtle spectral changes of various targets to be detected (Goetz et al., 1985) and are available for many applications, including the study of the spectral properties of forest canopies, few studies have been undertaken to identify tree species.

Many researchers have studied the spectral properties of trees. Most of those studies are based on spectra measured either from tree leaves only (e.g., Miller et al., 1991; Daughtry et al., 1989) or from selected compo-

nents of forest stands such as branches of needles, shoot stacks, barks, and litter and soil (e.g., Goward et al., 1994; Williams et al., 1991). Although this "decomposed" approach to spectral analysis has been valuable in understanding the biophysical and physiological characteristics of trees and quantifying the biochemical constituents of tree foliage, what has been learned from forest landscape components cannot be linearly scaled up to understanding the spectral characteristics of a forest canopy/stand as recorded in remotely sensed data. In order to characterize the spectral properties of forest canopies, a tremendous amount of effort to develop nonlinear models that are often complicated (e.g., Liang and Strahler, 1993; Li and Strahler, 1986) is required.

Differently from the "decomposed" approach to spectral analysis and radiative transfer modeling that integrate spectral properties of landscape components into the characterization of spectral properties of forest canopies, we undertook an explorative study on the potential of hyperspectral data, measured directly from above forest canopies in the field, for forest species recognition. We were motivated by 1) the belief that the rich amount of spectral information contained in hyperspectral data should improve the level at discrimination of forest species and 2) the desire for a relatively simple but robust method that can handle the large number of spectral bands in hyperspectral data while tolerant of spectral noise. In a preliminary study, a relatively small number of hyperspectra was collected from six conifer trees for species recognition. Results indicate that, with the spectral derivative technique and an artificial neural network algorithm, we can differentiate those conifer species at greater than 90% accuracies. This led us to conduct more experiments on species recognition using hyperspectral data collected in the field from more tree samples in California.

The objectives of this study are to 1) test a hypothesis that important conifer species in Northern California can be successfully recognized with *in situ* hyperspectral data, 2) further assess the capability of a neural network algorithm for conifer species identification, and 3) develop a band selection method. In this article, we report the procedures and preliminary results obtained to achieve the first two objectives.

STUDY AREA AND DATA COLLECTION

Study Area

Hyperspectral measurements were taken at the Blodgett Forest Research Station of the University of California, Berkeley, located in the American River watershed on the western slope of the central Sierra Nevada, El Dorado County, California. The elevation ranges from 1219 m to 1463 m and the slope ranges from 0% to 30%. The soils on the study area were formed from volcanic and intrusive igneous rocks. The area is classified as Site Quality I timberland. The climate is characterized by dry, warm summers and mild, wet winters. Blodgett Forest receives an average of 1650 mm of precipitation per year. The vegetation consists of the normal associates of the Sierra mixed conifer forest type, the major tree species include five conifers—sugar pine (SP, *Pinus lambertiana*), ponderosa pine (PP, *Pinus ponderosa*), white fir (WF, *Abies concolor*), Douglas fir (DF, *Pseudotsuga menziesii*), and incense cedar (IC, *Calocedrus decurrens*)—and one hardwood—California black oak (*Quercus kelloggii*). In addition, a species native to the Sierra Nevada but not found in the Blodgett Forest, giant sequoia (GS, *Sequoiadendron giganteum*), has been planted in selected sites since the early 1900s. Major shrub species include manzanita, deerbrush, white thorn, and bear clover.

Spectral Reflectance Collection

A high spectral resolution spectrometer, PSD1000 (dual spectrometer; ANCAL, 1995) was used to take measurements in the field. The spectrometer is designed for use with a portable computer. It may be used for precise measurements in various spectral ranges from 210 nm through 1050 nm. To provide full spectral coverage, PSD1000 has two spectrometers, master and slave. The master spectrometer covers the shorter spectral wavelength range (shorter than 700 nm) and the slave covers the longer spectral range (longer than 500 nm). The number of bands covered by the PSD1000 is more than 1500 with an average band width of 0.5 nm. The spectral resolution is approximately 2.6 nm. It is controlled by a portable computer allowing collected spectra to be displayed instantly or to be stored on storage media. The field of view of the spectrometer is approximately 22°. Three types of spectral measurements can be made: dark current (the response of the system with no light being exposed to detectors), white reference (spectra from a standard white panel with close to perfect diffusion), and sample (spectra obtained from the target of interest). To avoid saturation or shortage, an integration time for collecting photons is selected based on the illumination condition by adjusting the master/slave sampling frequency. A reflectance spectrum can be generated through dividing the sample radiance by the radiance from the standard white reference under the same light condition.

At Blodgett Forest, six sites—grazed (Site 1), hand-weeded (Site 2), hand-cut (Site 3), valley (Site 4), flat area (Site 5), and Sequoia (Site 6)—were chosen for hyperspectral measurements at different times in multiple years for long term monitoring of selected tree species. Canopy sizes at Sites 1–3 are smaller than those at Sites 4–6. Site 6 has the largest canopies with a dry soil background free of litter and understory vegetation. Sites 4 and 5 have more litter and understory vegetation sur-

Table 1. Hyperspectral Data Collected at Six Sites[a]

	DF		*GS*		*IC*		*PP*		*SP*		*WF*		*Sum*	
Site	N_t	N_s	N_t	N_s	N_t	N_s	N_t	N_s	N_t	N_s	N_t	N_s	N_t	N_s
1	10	20	10	20	10	20	10	20	10	20	10	20	60	120
2	6	12	9	18	2	4	4	8	7	14	4	8	32	64
3	5	10	4	8	5	10	5	10	5	10	5	10	29	58
4	1	10	1	10	1	10	1	10	1	10	1	10	6	60
5	3	6	3	6	3	6	3	6	3	6	3	6	18	36
6	5	10	5	10	5	10	5	10	5	10	5	10	30	60
Sum	30	68	32	72	26	60	28	64	31	70	28	64	175	398

[a] N_t=number of trees; N_s=number of samples.

rounding the tree canopies than all the other sites. The measurements used in this research are our first hyperspectral measurements over those sites. A total of 398 reflectance spectra were measured with the spectrometer between 20 and 21 October 1995, from six conifer species including DF, GS, IC, PP, SP, and WF. For measurement convenience, we selected young conifer trees (4–7 years old) at a height of shorter than 4 m. Measurements were taken at heights lower than 1.5 m. To analyze the effect of different light conditions, measurements were successively taken both from shaded and sunlit portions of tree canopies while holding the spectrometer sensor head 15–20 cm from directly above those canopies. During the period of measurement, the air temperature near the target measured varied from 25°C to 30°C with dry and mild wind conditions. The sky condition on 20 October varied from clear to scattered thin cloud cover. Dark current and white reference were measured every 5–10 min as necessary to minimize the effect of possible difference in illumination. On 21 October, the sky was clear. The measurement time on 20 October at Sites 1, 2, and 3 was from 12:50 to 14:00 local time and on 21 October from 12:30 to 14:00 for Sites 4, 5, and 6. Table 1 lists the numbers of spectral measurements for the six conifer species at the six different sites. We measured the spectral reflectances above some pure soil backgrounds at several sites. Since the soil type across all the sites is essentially the same, the results are as we expected, that their spectral differences are within 2%, a better than 10% relative error across all the sites.

METHODS

Use of an Artificial Neural Network Algorithm

A feed-forward neural network (NN) algorithm was used for species recognition. The network training mechanism is the error-propagation algorithm (Rumelhart et al., 1986). A neural network program developed by Pao (1989) has been adapted and used in this study. The network requires training using a certain number of samples of known species. After training is done, based on a minimum error criterion or an optimal test accuracy, the network can be used to classify new samples to tree species as its outputs. The NN algorithm has been explored by many researchers for classification using both remote sensing data and other kinds of data (e.g., Gong, 1996; Gong et al., 1996; McCormack et al., 1993; Yin et al., 1991; Hepner et al., 1990).

Discriminant Analysis

A linear discriminant analysis (DA) was tested for conifer species identification to compare with the NN. The procedure DISCRIM in the SAS package (SAS Institute, 1985) was used.

Accuracy Assessment

Of all the hyperspectral data collected, a small portion of samples was used to train the NN and/or the DA while the remaining portion was used to test the classifiers' discriminating power. We have generated a confusion matrix for each classification. However, there is no consistency among the patterns of misclassification when one confusion matrix is compared with another. Due to the explorative nature of this study, we shall only report the percentage correct recognition defined by the overall average accuracy (OAA):

$$OAA=\frac{n_c}{n_s}\cdot 100\%,$$

where n_c is the number of correctly classified samples and n_s is the total number of test samples used.

Experiments

A total of 398 original reflectance spectra were first smoothed with a five-channel Fast Fourier Transform smoothing routine (ANCAL, 1995). The reflectance values at shorter than 320 nm and longer than 930 nm wavelength regions were eliminated due to the weak response of the detectors for all study sites. To reduce the data volume, we merged and calculated the average value for every five consecutive bands instead of using the raw data. As a result, the smoothed reflectance spectrum has 226 bands. Spectral derivative was then taken from smoothed reflectance data. As illustrated in Gong

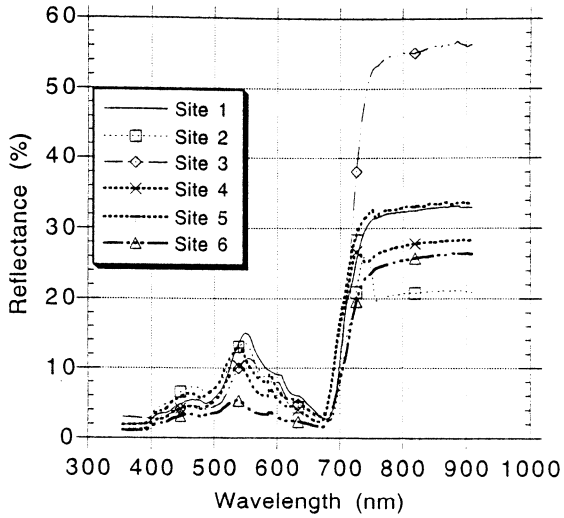

Figure 2. Reflectance curves collected from Douglas fir trees at six different study sites.

each tree species for training and all sunlit samples for testing.

Experiment 5: The Effects of Different Site Backgrounds
To test the effects of different site background on tree species identification, the six sites were divided into two groups based on their measurement dates. The first group (Group 1) includes Sites 1, 2, and 3, where the measurements were made on 20 October 1995, with scattered thin cloud cover for most of the time. The second group (Group 2) consists of Sites 4, 5, and 6, where the measurements were made on 21 October 1995 under a clear sky. Figure 2 shows the differences of reflectance spectra from the same species, Douglas fir, among the six different sites. For each group, the same tree species at different sites were treated as a different class. For example, species DF in Group 1 is divided into DF1 (for Site 1), DF2 (for Site 2) and DF3 (for Site 3), to evaluate the potential of identifying the same species at different sites. If the different classes of a tree species at different sites can be clearly separated, then the background spectra at different sites should be considerably different. Otherwise, their effects on tree species identification are weak. In each group, the samples belonging to the same tree species were randomly divided into two groups of approximately equal number of samples, one half for training and the other for testing.

Experiment 6: Evaluating the Discriminating Power of Different Wavelength Regions
To assess the discriminating power of different wavelength regions, we divided all the spectra into eight spectral ranges: blue-green (BG) covering 462–505 nm, green peak (GP) covering 536–580 nm, yellow edge (YE) covering 590–641 nm, red well (RW) covering 652–692 nm, red edge (RE) covering 700–744 nm, Visible covering 333–700 nm, and NIR1 covering 700–923 nm, and NIR2 covering 784–826 nm. In addition, a six-band subset selected from the center of spectral regions of BG, GP, YE, RW, RE, and NIR2 was used for species identification.

Experiment 7: Evaluating Reduced Number of Bands for Species Identification
Four schemes were designed to test reduced number of bands for species recognition. These are:

1. Average of smoothed bands (ASB): An ASB band was calculated by averaging every five consecutive smoothed bands resulting in 44 ASB bands from the original smoothed reflectance Bands 1–220.
2. Average of the first derivative bands (ADB): An ADB band was obtained by averaging every five consecutive first-order derivative bands, resulting in 44 ADB bands from the first derivative Bands 1–220.
3. Selection from smoothed bands by a fuzzy clustering algorithm (SSB): A fuzzy clustering algorithm (FCA) was introduced by Pu and Gong (1996) for hyperspectral band selection. An extensive assessment of FCA will be reported in another article. With this algorithm, 44 bands were selected from the smoothed bands (1–220).
4. Selection from first derivative bands with FCA (SDB): 44 bands were selected from first-order derivative bands (1–220).

RESULT ANALYSIS AND DISCUSSION

Spectral properties of forest canopies as observed with remote sensors are dependent of illuminating and atmospheric conditions (e.g., amount of shadow or shade), forest species, forest understory conditions (understory vegetation, soil, litter, etc.), seasonality, solar angle, viewing geometry, and the spatial resolution of the sensors. Change in any one of these variables could lead to changes in sensor responses to forest canopies and hence spectral indices derived from those sensor responses (Leblon et al., 1996; van Leeuwen and Huete, 1996; Qi et al., 1995; Huete et al., 1985). From the description on our spectral measurements, one can see that the effect of illumination and atmospheric condition is limited due to our frequent update of the measurements of the white reference and sensor dark currents. The viewing angle has been limited to nadir. The variation of solar elevation is limited to a small range as the time period during spectral measurements has been limited to around noon. The field of view has been limited to taking measurement only from canopies. The soil background was approximately the same. The season was late fall when the trees stopped growing. Therefore, measured spectral properties in this study represent primarily the characteristics of forest species (amount of leaves, leaf age, leaf-

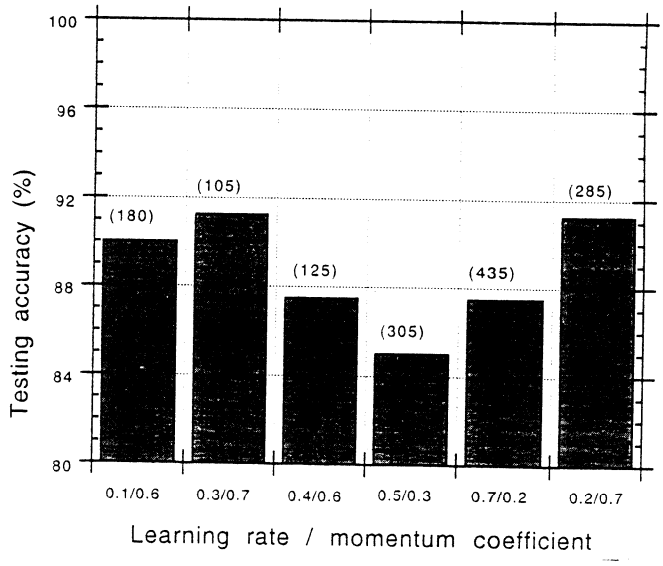

Figure 3. Comparison of test results from various combinations of learning rate (η) and momentum coefficient (a) for training the neural networks. Only one single hidden layer with 50 nodes and spectral derivative data with 222 bands were used. Forty training samples were randomly selected from spectral measurements at Site 1, and the remaining 80 samples were used as test samples. Numbers in parentheses are numbers of network training iterations.

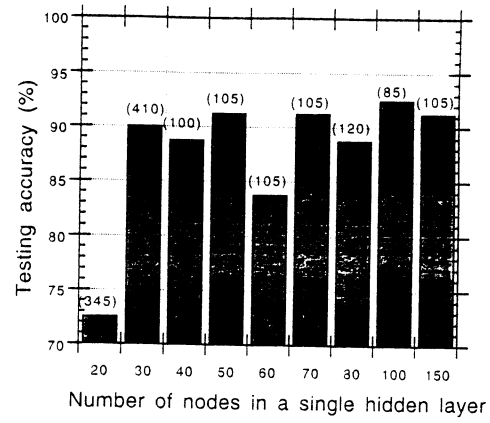

Figure 4. Neural network test results from various numbers of nodes in single hidden layer networks. η=0.3, a=0.7, and the inputs are 222 bands of derivative spectra. Data used were the same as in Figure 3. Numbers in parentheses are numbers of network training iterations.

branch ratio, leaf distribution, etc.) and the background/ hadow conditions. One would hope that the understory conditions remain the same, but in reality this is hard to find except the size of an area is small. Sometimes, the background conditions may not be a concern if the tree canopies are so large and dense that what has been measured is mainly from the canopies.

In this study, we have to deal with spectral measurements taken from forest canopies with varying conditions of background. A forest species characterized by *in situ* spectral measurements of tree canopies reflects the integrated effect of foliar chemistry, leaf shape and size, leaf amount, leaf age, and canopy structure. For the purpose of this research, if the spectral differences caused by such integrated effect are detectable, then hyperspectral remote sensing can be used to differentiate forest species. Therefore, we will limit our analysis to the integrated level. Further analysis requires a significant amount of knowledge of foliar chemistry and forest physiology that is beyond the scope of this paper.

Experiment 1

In order to test the effects of various η and a on the NN performance, we used first derivative data from Site 1 and randomly selected 40 samples for training and used the remaining 80 samples for testing. The NN had 50 odes in its hidden layer. η and a values were varied (Fig. 3). The best identification accuracy of 91% was obtained when η=0.2 or 0.3, a=0.7, and the number of nodes in the hidden layer was 50. A series of test results from six combinations of various (η, a) values(η varied from 0.1 to 0.7, while a from 0.2 to 07) were compared. All test accuracies are greater than 85%.

When using the same set of input data, η=0.3 and a=0.7, we assessed the effects of different number of nodes in the hidden layer on species recognition (Fig. 4). When the number of nodes in the hidden layer was changed from 20 to 150, the best overall average accuracy was 93% with 100 nodes, and the lowest accuracy was 73% with 20 nodes. The overall accuracies with 50, 70, and 150 nodes were the same (91%). Although slightly better accuracy (one more sample correctly classified) was achieved with 100 nodes, we prefer a 50-node hidden layer to the 70-, 100-, and 150-node ones because of its less computation requirement.

In our experiments, an NN with two hidden layers did not produce better results than those with a single hidden layer. Therefore, all remaining test results were generated from NNs with η=0.2 or 0.3, a=0.7 and one hidden layer with 50 nodes unless otherwise noted.

Experiment 2

Table 2 lists the results obtained from test samples in Experiment 2. For the NNs, better recognition accuracies in varied degrees were obtained for Sites 1–3 and 6 with first derivative spectra, while slightly better results were obtained from smoothed reflectance spectra for Sites 4 and 5. At Sites 1–3, the canopy sizes are smaller than those for Sites 4–6, and needle/leaf densities are also lower than those from Sites 4–6. The effect of background (mainly dry soils) at Sites 1–3 on measured spectra is greater than the mixture background (dry soils, grasses and litters) at Sites 4 and 5. Taking spectral de-

Table 2. Recognition Accuracies from Test Samples at Each Site[a]

Site	No. of Training Samples	No. of Testing Samples	NN		DA	
			Smooth Data	1st Deriv.	Smooth Data	1st Deriv.
1	40	80	55.00	91.25	83.75	77.50
2	32	32	59.38	81.50	71.88	65.63
3	30	28	64.29	71.43	71.43	57.14
4	30	30	73.33	70.00	76.67	66.67
5	18	18	66.67	61.11	50.00	55.56
6	30	30	70.00	73.33	70.00	70.00
Overall Accuracy (%)			62.39	79.39	74.77	68.81

[a] Training samples randomly selected and test samples not overlapping with training samples. NN=neural network identification; hidden layer nodes=50; learning rate=0.2; momentum coefficient=0.7; DA=discriminant analysis. Smooth data—226 bands; 1st deriv.—222 bands of first derivative data. Overall accuracy=number of correctly identified test samples/total test samples.

rivative can partly remove the effects of low frequency background soil spectra on target spectra. Therefore, use of derivative spectra can increase recognition accuracy. The spectral derivative processing may enhance high frequency noise caused by the inhomogeneous backgrounds at Sites 4 and 5 leading to decreased recognition accuracies at those sites. The effectiveness of spectral derivative seems to be significant for some sites (e.g., an increase in accuracy of 36.25% for Site 1). However, for Sites 4 and 5, direct use of smoothed reflectances produced slightly better results.

Although neural networks can work with a small ıber of training samples, our results indicate a very small number of training samples randomly selected lead to poor species recognition results due to the insufficient representativeness of the training samples. Thirty or more random samples produced stable results at each site in this study.

Because the use of second derivative spectra for species recognition did not produce better results than first derivative spectra, only results derived from first derivative spectra are presented here.

Examining the results from discriminant analysis, it can be seen from Table 2 that the use of original smoothed reflectances can usually generate better or equally well recognition accuracies as compared to those obtained from derivative spectra except for Site 5. This is because normal distribution is required for each band for each individual class to achieve optimal results with discriminant analysis. In general, the smoothed reflectance data for each tree species (class) would meet this requirement if the number of training samples is sufficient, but the spectral derivative data may not. The low recognition accuracy at Site 5 with smoothed spectra may be caused by the relatively smaller size (18) of training samples.

Comparing the two sets of better results from NNs d DA, we see that the best accuracies from NN are ..gher than those from DA at Sites 1, 2, 5, and 6, the same at Site 3, and lower at Site 4. It is interesting that DA outperformed NN at Site 4 where 60 samples were measured from only six trees of different species (Table 1). The increased number of samples per tree used for training may be more helpful to DA.

In general, the use of NN with derivative spectra as their inputs produced an overall accuracy of 79%, 4% higher than that produced by DA with smoothed reflectances as inputs. The recognition accuracies vary greatly across different study sites (e.g., the highest accuracies of 91% and 84% for site 1 from NN and DA, respectively; the lowest of 61% by NN and 50% by DA both at Site 5). Although this could be caused by variations of many factors including background, canopy density, time of measurement during the day, and illumination change, we think that the backgound is the major factor causing the low identification accuracies as explained at the beginning of this section. The variation in illumination on 20 October seemed to cause less a problem to the classifiers as data measured at two of the sites (1 and 2) on that day resulted in the highest accuracies. This is perhaps because training samples have well represented the illumination variations.

Experiment 3

When averages of shaded and sunlit spectra for each tree species were used, some better results were obtained (Table 3). Except Site 1, all recognition accuracies for Sites 2–6 increased 6–33% in comparison with the results presented in Table 2 with the same kind of classifier and the same derivative spectra. Better results from the use of average spectra of training samples may be obtained because averaged spectra may be more representative to each tree species than measured individual spectra. This is usually true when the total number of samples for each tree species is small. However, the overall average accuracy across all six sites is only 78%. At Site 1, the within-species spectral variability is greater due to the large number of samples collected and the longer time used during spectral measurement that could have involved more illumination variability. Large spectral variability will make the average spectra of samples less representative to all samples and that in turn will

Table 3. Test Accuracies Obtained from Neural Networks Trained with Average Spectra from Sunlit and Shaded Sides[a]

Site	*No. of Train Samples*	*No. of Test Samples*	*No. of Iterations*	*Test Accuracy (%)*
1	12	120	95	45.83
2	12	64	65	87.50
3	12	58	120	98.28
4	12	60	70	90.00
5	12	36	55	94.44
6	12	60	265	91.67
Overall accuracy (%)	—	—	—	78.14

[a] The same neural network structure was used with hidden layer nodes=50. Network input—first derivative spectra (222 bands). Learning rate=0.3; momentum coefficient=0.7. Overall accuracy=number of correctly identified samples/total number of samples.

lead to low identification accuracy. This is a potential problem with the use of average spectra in training.

Experiment 4

Table 4 lists the results obtained from sunlit spectra only. Although only one average spectrum from each class was used for training, higher recognition accuracies were achieved at four of the six sites when compared with the results in Table 3 except for Sites 2 and 3 where the accuracies are 4–5% lower. Compared with Table 3, the overall average accuracy was improved by 13–91%. The much increased overall accuracy, mainly caused by the improvement at Site 1, is quite satisfactory. It indicates that there is smaller differentiation among sunlit samples within the same tree species than that among both the shaded and sunlit samples.

Experiment 5

Table 5 lists the accuracies for site identification using spectra from the same tree species at different sites. An accuracy close to 0% would indicate that the spectra from the same tree species measured from different sites were not separable, implying that tree spectra were similar and independent of sites. A high accuracy has two implications. First, it may imply that contribution of background spectra and illumination change to tree spectra could still be large although first derivative spectra were used. Second, it may imply that the neural network algorithm is so sensitive to details that it can be used to discriminate subtle spectral differences among spectra collected from different trees (Gong, 1996). When the amount of leaf area is low and leaf orientation is close to the vertical direction, more background spectra may be collected by the spectrometer during the measurement of tree reflectances The effect of illumination change is stronger when the sun is blocked by scattered thick clouds from time to time during the spectral measurement. From Table 5, we can see that the identification of sites using spectral measurements from the same tree species is quite successful. Particularly, Douglas fir (DF), giant sequoia (GS), and white fir (WF) are good site indicators. This might be because the amount of leaves of PP is sparse and the leaf orientations of GS, WF, and DF point mostly upward making more background observed by the spectrometer. The incense cedar (IC) has resulted in consistently lower accuracies. This may be because IC leaves are thicker and most IC leaves are perpendicular to the spectrometer viewing direction, preventing much of the background spectra from being measured. It is reasonable to expect that spectral mea-

Table 4. Identification Accuracies from Sunlit Samples by NN Trained with the Average First-Derivative Spectra at the Sunlit Side[a]

Site	*No. of Training Sets*	*No. of Test Samples*	*No. of Iterations*	*Test Accuracies (%)*
1	6	60	50	90.00
2	6	32	30	84.38
3	6	29	35	93.10
4	6	30	80	90.00
5	6	18	15	100.00
6	6	30	30	93.33
Overall accuracy (%)	—	—	—	90.95

[a] NN has a structure of one hidden layer with 50 nodes. Learning rate=0.3; momentum coefficient=0.7. Overall accuracy=number of correctly identified sampels/total number of test samples.

Table 5. Separability of the Same Tree Species at Different Sites[a]

Tree Species	*No. of Training Samples*	*No. of Testing Samples*	*No. of Iterations*	*Testing Accuracy (%)*
	Among the Study Sites 1, 2 and 3 (Group 1)			
DF	22	20	30	95.00
GS	24	22	35	81.82
IC	18	16	25	75.00
PP	20	18	30	94.44
SP	22	22	100	81.82
WF	20	18	25	94.44
	Among Study Sites 4, 5, and 6 (Group 2)			
DF	14	12	15	100.00
GS	14	12	15	100.00
IC	14	12	20	75.00
PP	14	12	10	75.00
SP	14	12	15	91.67
WF	14	12	20	100.00
	Among All Six Sites (All Sites)			
DF	34	34	40	91.18
GS	36	36	255	77.78
IC	30	30	50	70.00
PP	32	32	105	96.88
SP	36	34	40	82.35
WF	32	32	45	93.75

[a] NN has a structure of one hidden layer of 50 nodes. Network input—first derivative spectra (222 bands). Learning rate=0.2 or 0.3; momentum coefficient=0.7.

surements made from off-nadir directions may reduce the effect of background. This requires further experiments.

The separability among tree spectra of the same tree species are 100% correct for species DF, GS, and WF in Group 2. This implies that the effect of background spectra on tree spectra may be especially large when the tree spectra were measured under clear sky condition (on 21 October). The spectral differences of the background at different sites could be greater than the differences in tree spectra of the same species. As a result, the measured tree spectra may actually be described mostly by various background components (e.g., dry soils, grasses, litters, and staking). This is especially true for those spectra taken from small tree canopies with sparse needle-leaves. The site identification accuracies obtained from spectral measurements of 20 October (Group 1) are lower than those on 21 October (Group 2) under clear sky condition. The accuracy differences could be caused by the different separabilities among the two groups of sites and/or the differences in illumination conditions between the two days. Since this effect can be reduced when derivative spectra collected under the same site background are used, a higher species recognition accuracy can still be observed from previous experiments.

We conducted a preliminary experiment on within species separability at the same site to examine the effect of network sensitivity. Site 1 was selected for the experiment. The highest overall accuracy for tree species recognition at Site 1 implies that the samples have less within class variability. Since we have 20 samples from 10 trees of the same species, we randomly divided the 10 trees into two groups of five trees and treated them as two different classes. From each group of trees, we then randomly selected five spectral samples for training and the remaining five samples for testing a neural network. The test accuracy, as an indicator of within-species separability, was then calculated for each tree species to see how a network can separate the tree spectra obtained from two arbitrarily assigned classes of the same tree species. The average of the accuracies so determined for the six tree species is 61%. This indicates that the neural network algorithm is indeed very sensitive and can be trained to discriminate finer details. The result has complicated implications to the interpretation of the site differentiation results presented above and to the extrapolating capability of the algorithm for species identification when networks are trained using data from one site and tested at different sites. Networks sensitive to fine spectral details, noted as "overtrained elsewhere (e.g., Gong, 1996), may lose extrapolation capability. These implications will be further studied.

Experiment 6

From Table 6, it can be seen that recognition accuracies with visible bands (140 bands) are consistently better than those from NIR1 bands (82 bands) for every study

Table 6. Identification Accuracies from Nine Band Groups[a]

Site	No. of Training Samples	No. of Test Samples	BG (462–505 nm)	GP (536–580 nm)	YE (590–641 nm)	RW (652–695 nm)	RE (700–744 nm)	Visible (333–700 nm)	NIR 1 (700–923 nm)	NIR 2 (784–826 nm)	Six-Band
1	40	80	88.75	45.00	42.50	48.75	46.25	95.00	52.50	41.25	43.75
2	32	32	50.00	31.25	34.38	56.25	56.25	62.50	56.25	37.50	40.63
3	30	28	57.14	39.29	50.00	32.14	42.86	85.71	42.85	35.71	35.71
4	30	30	43.33	40.00	46.67	40.00	60.00	66.67	60.00	30.00	43.33
5	18	18	50.00	55.56	16.67	27.78	72.22	50.00	50.00	66.67	38.39
6	30	30	50.00	53.33	43.33	36.67	36.67	80.00	50.00	50.00	56.67
Overall acc. (%)	—	—	64.22	43.58	40.83	43.12	50.00	79.36	52.29	41.74	43.54

[a] NN structure: a hidden layer of 50 nodes for visible and NIR1, 10 nodes for all other band groups. Input was first derivative spectra; learning rate=0.2; momentum coefficient=0.7. Visible has 140 bands, NIR 1 has 82 bands, and all other groups have 18 bands except the six-band group. BG: blue-green, GP: green peak, YE: yellow edge, RW: red well, RE: red-edge. Overall acc.=number of correctly identified test samples/total test samples. Underlines indicate the highest accuracy at a site among those band selections.

site when the same training samples and test samples were used. The more spectral variability in the visible region resulted in larger variation in derivative values than those from NIR1. The larger variation in the derivative spectra contributed more to tree species identification. The recognition accuracies for Sites 1, 3, and 6 in Table 6 are greater than the corresponding ones obtained from all the spectral bands (Table 2). This indicates that many spectral bands may not be necessary for species recognition. A lot of spectral bands may not only introduce more noise but also increase the amount of computation.

Among the six spectral regions of 18 bands each, the highest overall accuracy of 64% was obtained with the blue to green (BG) region. The red-edge (RE) region ranks the second (50%) and the yellow edge region ranks the lowest accuracy (41%). The results indicate that the blue-edge (BG) of the green peak may be more important than the red-edge of tree spectra in discriminating tree species. Since the BG region is also more affected by the atmospheric interference due to its shorter wavelength, its effectiveness in airborne and spaceborne remote sensing should be further assessed. Although there are only six bands in the six-band group, the recognition accuracy (44%) is close to that (42%) of GP and NIR2 regions both having 18 bands. The results from this experiment indicate that some bands are more important than others in tree species identification. Therefore, selecting a smaller number of bands while preserving as much discriminating power as possible is an important task in tree species identification.

Experiment 7

With the same set of data, that is, both smoothed data and first-order derivative spectra from Site 1, the same network structure, that is, $\eta=0.3$, $\alpha=0.7$, and 20 or 30 nodes in the hidden layer, we tested four different schemes of band reduction. Table 7 lists the better results achieved from either the use of 20 or 30 hidden-layer nodes for each set of the 44 input features obtained from a band reduction scheme. For the smoothed spectra, higher recognition accuracies (63% and 69%) were obtained by the use of band reduction as compared with the use of all bands (i.e., 55% in Table 2). The averaging of derivative data resulted in poorer accuracies (81%) than the use of all derivative bands (i.e., 91% in Table 2). This is understandable because averaging could remove a lot of differential information as contained in the original derivative data. When the FCA was used to the derivative data, the best recognition results (98%) were obtained. More than half of the 44 derivative bands selected by the FCA are in the ultraviolet to blue region and approximately 30% in the near infrared region. This indicates that derivative bands in those regions have stronger discriminating power than those in the green, red, and red-edge regions. This experiment proves that

Table 7. Identification Accuracies of Some Subsets of Bands from Site 1[a]

Scheme	*No. of Training Samples*	*No. of Test Samples*	*No. of H-Layer Nodes*	*No. of Iterations*	*Accuracy (%)*
ASB	40	80	20	655	62.50
ADB	40	80	30	215	81.25
SSB	40	80	30	590	68.75
SDB	40	80	30	185	97.50

[a] NN structure: 1 hidden layer, learning rate=0.2, momentum coefficient=0.7, input nodes=44.
H-Layer=hidden layer. Scheme abbreviations, see text.

better accuracies are obtainable with a smaller number of spectral bands than the use of all bands and led us to undertake more detailed experiments on the comparison of various band selection methods. Results will be presented in a separate article.

SUMMARY AND CONCLUSIONS

We reported experiments undertaken to classify six conifer species from hyperspectral measurements taken in the field. Instead of analyzing spectral properties measured from individual landscape components such as tree leaves, branches, litter, bark, soils, grass, and shrubs, we analyzed spectra taken directly from above tree canopies. We believe that this analysis of *in situ* tree spectra measured at the "integrated canopy level would provide ore direct insights to the practical use of remote sensing.

We tested an artificial neural network algorithm and linear discriminant analysis for conifer species identification. The hyperspectral data were measured from six sites at the Blodgett Forest Research Station of the University of California at Berkeley, located in the western slopes of Sierra Nevada. The six conifer tree species are Douglas fir, giant sequoia, incense cedar, ponderosa pine, sugar pine, and white fir. Raw hyperspectral data were processed to form two types of data for species identification, smoothed reflectances, and first derivative spectra. We tested species recognition using samples from each of the six study sites.

With neural networks applied to first derivative data from all spectral bands, the overall average identification accuracy calculated from test samples was 79% when about 45% of the total samples were used to train neural networks and the remaining 55% were used for testing. This overall accuracy is 17% higher than the use of smoothed reflectances with the neural networks. It is 10% higher than the use of linear discriminant analysis when exactly the same data were used. With linear discriminant analysis applied to the smoothed data, the overall average accuracy was 75% with the same set of training and testing samples as those used for the neural networks.

The use of average spectra of all samples for a particular tree species in training with the neural networks applied to first derivative data resulted in an overall accuracy of 78% when all 398 samples were used as test samples. Use of only average sunlit samples for neural network training resulted in an overall accuracy of 91% when all the 199 sunlit samples were used as test samples. This represents the most successful identification of the six conifer species.

The effects of background spectra and illumination change on tree species spectra among different sites can be large, especially when the canopy leaves are sparsely distributed and the leaf orientation makes background to be observed easily from nadir direction. Further study should be made to separately analyze the effects of background and illumination changes on hyperspectral measurements for tree species identification.

The discriminating power of the visible region is stronger than the near-infrared region. With the visible region alone, an overall accuracy of 79% was achieved with the neural networks. When six physically meaningful spectral regions were compared for tree species recognition, the 18-band blue-green spectral region resulted in an overall accuracy of 64%. With 82 near-infrared bands, the overall accuracy was only 52%. Some initial results on band selection prove that a smaller number of spectral bands can produce better accuracies than the use of all the bands. A challenging task is to select the appropriate spectral bands for different purposes with a limited number of samples.

Our experiments indicate that the six conifer species studied in this research can be identified with high accuracy based on spectral measurements made at sunlit sides of tree canopies under stable illumination conditions. Only when more analysis is done to spectral measurements made from more conifer species and in different seasons and cross validations both in space and in time are done, will we accomplish our test of the hypothesis posed at the beginning of the Introduction. A companion article is under preparation that deals with the spectral measurements in early spring, summer, and fall at those study sites. One of the conclusions in that article is that differences in solar elevation in different seasons do not have a significant effect on the performance of the classifiers for the identification of the six species.

Collaboration with other scientists is underway to conduct leaf biochemical analysis of giant sequoia, a species less studied biochemically and physiologically. This could provide insights to our hyperspectral analysis. Hyperspectral data acquired from airborne and satellite platforms will also be tested for conifer species identification.

REFERENCES

ANCAL, Inc. (1995), *C-SPEC Data Acquisition and Manipulation Program, Users Guide & Operating Instructions, Version 1.5*. Ancal, Inc., Las Vegas.

Boardman, J. W. (1989), Inversion of imaging spectrometry data using singular value decomposition. In *Proceedings of the IGARSS'89*, Vancouver, BC, Canada, pp. 2069–2072.

Card, D. H., Peterson, D. L., and Matson P. A. (1988), Prediction of leaf chemistry by use of visible and near infrared reflectance spectroscopy. *Remote Sens. Environ.* 26:123–147.

Curran, P. (1989), Remote sensing of foliar biochemistry. *Remote Sens. Environ.* 30:271–278.

Daughtry, C. S. T., Biehl, L. L., and Ranson, K. J. (1989)., A new technique to measure the spectral properties of conifer needles. *Remote Sens. Environ.* 33:55–64.

Goetz, A. F. H., Vane, G., Solomonson, J. E., and Rock, B. N. (1985), Imaging spectrometry for earth remote sensing. *Science* 228:1147–1153.

Gong, P. (1996), Integrated analysis of spatial data from multiple sources: using evidential reasoning and an artifical neural network for geological mapping. *Photogramm. Eng. Remote Sens.* 62(5):513–523.

Gong, P., Pu, R., and Miller, J. R. (1992), Correlating leaf area index of ponderosa pine with hyperspectral CASI data. *Can. J. Remote Sens.* 18(4):275–292.

Gong, P., Miller, J. R., and Spanner, M. (1994), Forest canopy closure from classification and spectral unmixing of scene components—multisensor evaluation of an open canopy. *IEEE Trans. Geosci. Remote Sens.* 32(5):1067–1080.

Gong, P., Pu, R., and Miller, J. R. (1995), Coniferous forest leaf area index estimation along with Oregon transect using Compact Airborne Spectrographic Imager data. *Photogramm. Eng. Remote Sens.* 61(9):1107–1117.

Gong, P., Pu, R., and Chen, J. (1996), Mapping ecological land systems and classification uncertainties from digital elevation and forest cover data using neural networks. *Photogramm. Eng. Remote Sens.* 62(11):1249–1260.

Goward, S. N., Huemmrich, K. F., and Waring, R. H. (1994), Visible-near infrared spectral reflectance of Landscape components in western Oregon. *Remote Sens. Environ.* 47:190–203.

Hepner, G. F., Logan, T., Ritter, N., and Bryant, N. (1990), Artificial neural network classification using minimal training set. *Programm. Eng. Remote Sens.* 56:469–473.

Huete, A. R., Jackson, R. D., and Post, D. F. (1985), Spectral responses of a plant canopy with different soil backgrounds. *Remote Sens. Environ.* 17:37–53.

Johnson, L. F., Hlavka, C. A., and Peterson, D. L. (1994), Multivariate analysis of AVIRIS data for canopy biochemical estimation along the Oregon Transect. *Remote Sens. Environ.* 47:216–230.

Leblon, B., Gallant, L., and Granberg, H. (1996), Effects of shadowing types on ground-measured visible and near-infrared shadow reflectances. *Remote Sens. Environ.* 58:322–328.

Li, X., and Strahler, A. (1986), Geometric-optical bi-directional reflectance modeling of a coniferous forest canopy. *IEEE Trans. Geosci. Remote Sens.* GE-24:906–919.

Liang, S., and Strahler, A. H. (1993), An analytic BRDF model of canopy radiative transfer and its inversion. *IEEE Trans. Geosci. Remote Sens.* 31(5):1081–1092.

Matson, P. A., Johnson, L. F., Miller, J. R., Billow, C. R., and Pu, R. (1994), Seasonal patterns and remote spectral estimation of canopy chemstry across the Oregon Transect. *Ecol. Appl.* 4(2):280–298.

McCormack, M. D., Zaucha, D. E., and Dushek, D. W. (1993), First-break refraction event picking and seismic data trace editing using neural networks. *Geophysics* 58:67–78.

Miller, J. R., Wu, J., Boyer, M. G., Belanger, M., and Hare, E. W. (1991), Season patterns in leaf reflectance red edge characteristics. *Int. J. Remote Sens.* 12:1509–1523.

Pao, Y. (1989), *Adaptive Pattern Recognition and Neural Networks*, Addison and Wesley, New York, pp. 113–299.

Pu, R., and Gong, P. (1996), Band selection from hyperspectral data using a fuzzy clustering technique for tree species identification. In *Proceedings of Geoinformatics '96*, West Palm Beach, FL, pp. 464–471.

Qi, J., Moran, M. S., and Dedieu, G. (1995), Normalization of sun/view angle effects using spectral albedo-based vegetation indices. *Remote Sens. Environ.* 52:207–217.

Rumelhart, D. E., Hinton, G. E., and Williams R. J. (1986), Learning internal representations by error propagation. In *Parallel Distributed Processing-Explorations in the Microstructure of Cognition* (D. E. Rumelhart and J. L. McClelland, Eds.), MIT Press, Cambridge, MA, Vol. 1, pp. 318–362.

SAS Institute, Inc. (1985), *SAS User's Guide: Statistics*, 5th ed., Cary, NC.

van Leeuwen, W. J. D., and Huete, A. R. (1996), Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices. *Remote Sens. Environ.* 55:123–138.

Williams, D. L. (1991), A comparison of spectral reflectance properties at the needle, branch, and canopy level for selected conifer species. *Remote Sens. Environ.* 35:79–91.

Yin, Y., and Xu, X. (1991), Applying neural net technology for multi-objective land use planning. *J. Environ. Manage.* 32:349–356.