Band Selection from Hyperspectral Data for Conifer Species Identification

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Abstract

Hyperspectral data compression and dimension reducing are very important to computer processing and data transmission. A small number of bands, containing relatively large amount of spectral information, are usually sufficient to many application purposes. Therefore, how to select a small number of bands without loss of much information from all the bands is a critical issue. In this paper, a method of band selection using band prioritization with peak values of sum of 30-eigenvector pertinent to principal component analysis (PCA) was developed. An error back-propagation neural network (NN) algorithm was applied to evaluate the effectiveness of the band selection method in forest species recognition. The results show that, when entering NN with 6-20 bands selected from a total of 161 bands of hyperspectral data for identifying six conifer species, the average recognition accuracy improvement of 11.20% can be obtained using the new band selection method over the method of equal-interval band selection.

I. INTRODUCTION

Hyperspectral data with hundreds of spectral bands in very narrow intervals allow us not only to measure diagnostic spectral features in geology survey (Goetz et al., 1985) but also to estimate biophysical and biochemical parameters such as leaf area index (LAI) (e.g., Gong et al., 1995 and 1992), conifer species identification (e.g., Gong et al., 1997 and Yu et al., 1999), biochemical constituents (Card et al., 1988; Johnson et al., 1994; Matson et al., 1994; Peterson et al., 1988; and Wessman et al., 1989), and decomposition of spectral mixture pixels (Boardman, 1989 and Gong et al., 1994). as well as to apply to other fields (e.g., atmosphere). But such data, compared to multispectral data, create enormous amounts of data for computer processing and data transmission. To mitigate this problem, a data compression is generally used to reduce data volume (Chang et al., 1999). And a variety of feature extraction techniques can also be used to reduce data magnitude (e.g., band subset directly selected from total bands and Karhunen-Loeve (i.e., hereafter called principal component analysis, PCA) transformation in spectral dimension). In existing band selection methods, we can generally classify them into two categories: bands selected based on class separability or prediction effectiveness with the subset of bands and based on band prioritization related to PCA transformation. For examples, in the first category, Hardie et al. (1998) selected spectral bands based on a class separability criterion. They exhaustively search over all band combinations using a separability metric to yield an optimal K (k<N, total bands) band combination. A search of a k-band combination with this method often needs long time, especially when k is greater. The best band combination selected by a stepwise regression procedure is another way to get subset of bands. Coleman et al. (1991) found the best combination of bands, which efficiently quantifies selected properties in highly weathered soils, based on stepwise regression procedure. The two methods to search the optimal band combination did not consider removal of correlation among the selected bands. Zhang (1994) studied five band selection methods for testing the sensitivity of linear spectral unmixing of forest species. All five methods did not remove majority of correlation among the selected bands mainly because separability among the end species and background were used as a criterion. The second type of band selection method is studied more extensively. Csillag et al. (1993) classified salinity status of soils based on hyperspectral data selected using a modified step-wise principal component analysis. In their study, the correlation among the original bands chosen did not decrease as efficiently as the "conventional" PCA. Thus there is still redundant information among the bands selected. The method proposed by Henderson et al. (1989) was based on the greatest magnitude of eigenvectors and they selected important wavelength region corresponding to the magnitude of eigenvectors. As a result, there is a greater correlation among the bands selected by the method. Chang et al. (1999) researched on a joint

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band prioritization and band-decorrelation approach to band selection for hyperspectral image classification. The band prioritization was based on an eigenanalysis and decomposed a matrix into an eigenform matrix from which a loading factors matrix could be constructed and used to priorize bands. The band prioritization was then followed by a divergence-based band decorrelation that used the divergence measure to remove redundant or insignificant bands. Their approach is a better one because they ranked band prioritization not only considering the bands selected with the greatest amount of signal but also removing correlation and noise among and within bands selected as completely as possible.

In this paper, we propose a band selection method in part similar to one by Chang et al. (1999) but in a different and simple way to remove the correlation among the bands selected and to maintain a higher amount of spectral signal in bands selected. The band selection method based on band prioritization pertinent to PCA transformation was used to classify six conifer species from SD1000 spectrometer data acquired from Blodgett Forest Research Station, Department of Environmental Science, Policy and Management, University of California at Berkeley. The objectives of this study are:

- to develop a band selection method based on band prioritization pertinent to PCA; and
- to evaluate the effectiveness of this method using an error back-propagation neural network (NN) algorithm for conifer species recognition.

II. DATA SOURCES AND METHODOLOGY

In Situ Hyperspectral Data Acquisition

In situ hyperspectral data were taken with an SD1000 spectrometer at Fenced site, Blodgett Forest Research Station at four dates of 1997: May 20, July 21, September 23, and November 28, 1997. Under the natural light condition, only spectral reflectance data between 350 and 900 nm in 980 bands can be employed. Outside this range, spectral data are too noisy to be used. The spectral resolution is approximately 2.6 nm. At each date, we took a total of 144 spectra from six conifer species: Douglas fir, giant sequoia, incense cedar, ponderosa pine, sugar pine and white fir, with each measuring six trees and taking four samples per tree, two from sunlit side and other two from shaded side.

For the purpose of this paper we first merged and calculated average per six consecutive bands and led to 163 merged bands with a band width of 3.4 nm. Then every spectrum r_i was normalized through $r'_i=r_i/\sum(r_i)$. Finally, the first-order derivative of each spectrum was calculated from the normalized spectrum for testing the band selection method. Each available spectral sample includes 161 bands.

Band Selection with Band Prioritization Pertinent to PCA

PCA technique has been widely applied in data compression and feature extraction. It transforms data coordinates in such a way that first principal component vector is along the direction of maximum variance. It then maximizes the variance in successive components.

Suppose a data-sample covariance matrix can be obtained through following expression:

$$\Sigma = \frac{1}{N}\sum_{k=1}^{N}(X_k - m)(X_k - m)^T \qquad (1)$$

where, X_k is the kth l-dimension spectral vector, m is sample-mean vector, N is the total number of spectra, and l is the data dimension (i.e., total number of bands). Since the Σ is a symmetric and nonnegative definite matrix, all its eigenvalues $\{\lambda_i\}_{i=1}^{l}$ are real and nonnegative, and its corresponding l-dimensional eigenvectors $B_i = (\beta_{i1}, \beta_{i2}, ..., \beta_{il})^T$ for $i = 1, 2, ..., l$ can be chosen to be orthonormal. we can define loading factors γ_{ik} associated with B_i for PCA transformation as

$$\gamma_{ik} = \sqrt{\lambda_i}\beta_{ik} \qquad \text{for } k = 1, 2, ..., l. \qquad (2)$$

Based on Chang et al. (1999), for each $k = 1, 2, ..., l$, ρ_k defined by

$$\rho_k = \sum_{i=1}^{l}\gamma_{ik}^2 \qquad (3)$$

is indeed the variance σ_{kk}^2 of the kth band samples. Summing up γ_{ik}^2 over k in (3) for each $i = 1, 2, ..., l$ also yields

$$\lambda_i = \sum_{k=1}^{l}\gamma_{ik}^2 . \qquad (4)$$

So from (3) and (4), $\sum_{k=1}^{l}\rho_k = \sum_{i=1}^{l}\lambda_i$.

Since (3) also represents variance σ_{kk}^2 of the kth band samples, we can define $\rho'_k = \sum_{i=1}^{m}\gamma_{ik}^2$ to be an approximately variance σ_{kk}^2 of the kth band samples when the cumulative contribution rate of the first m ($m<l$) principal components can account for the majority of total variance of samples (e.g., greater than 95%). From all ρ'_k for $k = 1, 2, ..., l$, we can always find s ($s<l$) bands corresponding to peak values of ρ'_k, which defined as following:

if $\rho'_{j-1} < \rho'_j > \rho'_{j+1}$ for $j = 1, 2, ..., l$. (5)

then jth band is selected as one corresponding to peak values of ρ'_k . Without loss of generality, we can assume that $\rho'_1 \geq \rho'_2 \geq ... \geq \rho'_s$. Although we can not select the first s highest-ρ'_k bands to be equivalent to finding s principal variables with $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_s$, we maintain a selection of suboptimal band combination, and at same time also keep a low correlation among the bands selected because we did not select those neighbor bands, between which there generally exists a higher correlation. This is particularly true for hyperspectral data (Jia and Richards, 1994). For practical purposes, if only needing number of bands less than s like in this paper, we may select the first several bands based on the band prioritization with $\rho'_1 \geq \rho'_2 \geq ... \geq \rho'_s$. To test the function of individual eigenvectors in band selection, we also found out the bands corresponding to absolute peak values of the first several eigenvectors and selected bands based on the band prioritization similar to the above. Because band selection is based on the band prioritization with peak values pertinent to eigenvectors of PCA, we briefly name the band selection method as BPPCA.

Back-Propagation Neural Network

The supervised error back-propagation neural network (NN) algorithm is used to evaluate the effectiveness of the band selection method with BPPCA. In Pao (1989), a supervised NN algorithm is introduced in details. The NN algorithm has been explored by many researchers on classification using both remote sensing data and other kinds of the data (e.g., Hepner et al., 1990; Yin et al., 1991; Chen et al., 1993; Gong, 1996; and McCormack et al., 1993).

In this study, because there is not a more effective method that can be applied to evaluate the effectiveness of band selection for recognizing conifer tree species, the NN algorithm was used to generate identification accuracy of tree species with 6 to 20 bands selected by BPPCA. Different accuracies of tree species recognition were produced by the NN using testing samples, with same parameters adjusted during the training of the NN. These include learning rate(η), momentum coefficient (α), number of hidden layer nodes etc.(Rumelhart et al., 1986). Various numbers of bands selected with BPPCA were input to the NN. In the meantime, the species recognition accuracies of bands selected with an equal-interval band selection (EIBS) were calculated by NN with the same parameters and the same number of bands. The accuracy differences between those by BPPCA and those by EIBS were then compared.

Procedure

The following procedure was used in this study:

- Step 1. Prepare data for calculating covariance matrix for each data set of 4 dates, including merging original bands, light normalization, the first derivative and mean vector calculation.
- Step 2. Solve the K-L equation for each data set to calculate its eigenvalues and corresponding eigenvectors.
- Step 3. Separately calculate $\rho'_k = \sum_{i=1}^{m} \gamma_{ik}^2$ for each data set and find bands corresponding to peak values of ρ'_k, then rank band prioritization with $\rho'_1 \geq \rho'_2 \geq ... \geq \rho'_s$. In this study, m=30, i.e., using 30 eigenvectors. For testing individual eigenvectors, the bands corresponding to absolute peak values of the first several eigenvectors were found and band prioritization was ranked with the same way as that using 30 eigenvectors.
- Step 4. Select bands based on the band prioritization generated at step 3. Select different numbers of band subsets, from 6 to 20 bands, with BPPCA 30-eigenvector, individual eigenvectors and EIBS, respectively.
- Step 5. Calculate accuracies of tree species identification from selected band subsets with different numbers of bands using the NN and the test samples of each data set. Three sets of recognition accuracies, in the same time, were obtained: two were for band subsets selected with BPPCA and the other for those bands chosen with EIBS. In calculation, the parameters used for running NN for the three sets of selected bands were the same. For each NN, training continued to be executed until the highest identification accuracy from test data set was reached.
- Step 6. Analyze identification accuracies. For every three band subsets from BPPCA and EIBS, the identification accuracies were compared.

III. RESULTS AND ANALYSIS

Input the four data sets each with 144 spectra and each spectrum with a total of 161 bands for executing principal component analysis with an SAS procedure PRINCOMP (SAS Institute, Inc., 1991). Figure 1 presents four the first eigenvector from the four data sets and Figure 2 shows sum of 30 square loading factors from 30-eigenvector. From Figures 1 and 2, the wavelength positions corresponding to peak values are very consistent among the four data sets. This indicates that more important bands are basically same among the four data sets. After taking a close look at those curves, the greater peak values can be found to locate in red edge (670-726 nm), blue edge (490-530 nm) and green peak (540-565 nm). This is agreement with the conclusion drawn from our previous work

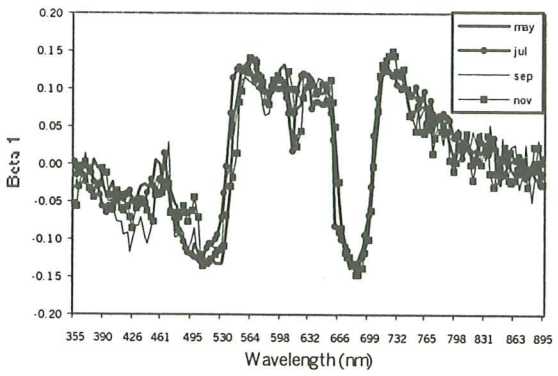

Figure 1. The first eigenvector for four data sets.

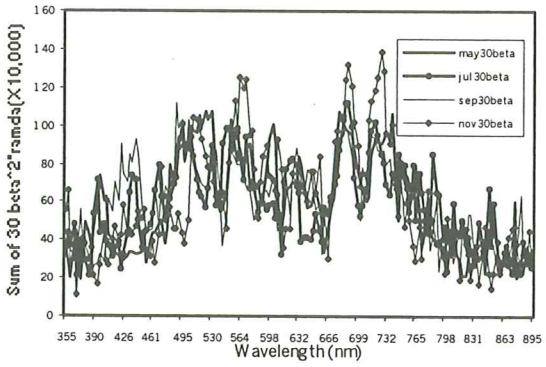

Figure 2. Sum of 30 square loading factors from 30-eigenvector

(Gong et al., 1997), i.e., the spectra within visible region may contain more spectral information than that in near infrared region. The contribution and cumulative contribution rates of the first three and the first thirty eigenvectors are listed in Table 1. From the table, the total variances for the four data sets can be accounted for >50%, >67% and >95% by the first one, three and thirty eigenvectors, respectively. According to peak-value-based band prioritization, different numbers of band subsets were selected from 30-eigenvector and individual eigenvectors (first three), respectively. For bands selected from individual eigenvectors, the numbers of bands each selected from the first three eigenvectors followed Table 2. As a result, the numbers of band selected with BPPCA and EIBS range from 6 to 20.

The NN using the GDR was adapted from Pao (1989). Structure of neural network of three layers was used for recognizing tree species. The numbers of nodes in the input layer were the numbers of bands selected (i.e. a node = a band). The numbers of nodes at hidden layer were 10 or 15. The six nodes in the output layer corresponded to six tree species. Other NN parameters were adopted after trial and error: learning factor (η) = 0.2, momentum rate (α) = 0.6 or 07, and number of iterations was less than 2000. For the four data sets, each was divided into two subsets: one for training NN, 48 samples, and other for testing the trained NN, 96 samples. The data in the input layer and output layer were normalized to the range of [0,1] to make it easier for NN to converge at the training stage. The recognition accuracies were calculated from the classification results using test samples compared to actual tree species recorded when taking measurements in the field.

In this study, the testing results in Table 3 were obtained from the NN with different numbers of bands selected from the four data sets and different band selection methods. From the table, although the accuracies from 30-eigenvector are not always the highest for all numbers of bands selected from all individual data sets, we can see that for all numbers of bands selected with BPPCA from 30-eigenvector, the average identification accuracies from the four data sets are higher than (average increasing 11.20%) those from EIBS. And those from singular eigenvectors are also higher than (average increasing 7.00%) those from EIBS except 20 bands selected. With BPPCA 30-eigenvector, the optimal results were generated from Sep'97 data with average accuracy increased 24.43% compared to that with EIBS and the least improvement was related to Nov'97 data. When we consider advantages from BPPCA 30-eigenvector, this is because bands selected based on band prioritization with peak values of sum of 30-eigenvector can not only account for majority of total variances

Table 1. Contribution and cumulative contribution rates of the first thirty eigenvectors

Eigenvector	May' 97		Jul' 97		Sep' 97		Nov' 97	
	Con.	Cum.-Con.	Con.	Cum.-Con.	Con.	Cum.-Con.	Con.	Cum.-Con.
β_1	0.5459	0.5459	0.5355	0.5355	0.4959	0.4959	0.5346	0.5346
β_2	0.0727	0.6186	0.0963	0.6318	0.1282	0.6241	0.0818	0.6164
β_3	0.0629	0.6815	0.0430	0.6748	0.0636	0.6877	0.0540	0.6704
□	...	...	...	...	...	...	...	...
β_{30}	0.0031	0.9506	0.0028	0.9476	0.0030	0.9481	0.0023	0.9606

Note: Con.--contribution rate; Cum.-Con.--cumulative contribution rate.

Table 2. Number of bands selected based on singular eigenvectors

# band	β_1	β_2	β_3
6	6		
8	6	2	
10	6	4	
12	6	4	2
14	6	6	2
16	8	6	2
18	10	6	2
20	10	6	4

included in spectral samples but also reduce or remove the correlation between the bands selected. Since using only the first three eigenvectors that account for about 67% of total variance, the accuracies with bands selected from singular eigenvectors were not high as those from 30-eigenvector. For the unstable results with BPPCA 30-eigenvector from Nov'97, May'97 and Jul'97 data, it can be explained as bands selected without de-noise that might result in lower accuracies, especially when the number of bands selected is close to 20.

In general, if band selection is simply made using EIBS, then more redundant information maybe included, which does not offer much help in tree species recognition. In addition, the phenomenon of relatively large correlation among bands can clearly produce lower accuracy for recognizing tree species compared to BPPCA. We are not able to explain why the identification accuracies with 18 bands from May'97 data, 20 and 14 bands from Nov'97 data selected by the EIBS were higher than those with BPPCA. An explanation to this might be that all possible subsets of bands selected in the randomly sampling method (EIBS is a kind of random band selection method) involve some band subsets that can be effectively used for recognizing tree species, even better that with BPPCA. However, most of these band subsets are less effective compared with those from the BPPCA method. Therefore, according to our experimental results, if the number of bands selected is less than 20 bands, the BPPCA 30-eigenvector method used in this study is effective for recognizing tree species.

IV. SUMMARY

In this paper, a band selection method using band prioritization with peak values of sum of 30-eigenvector pertinent to PCA was developed to recognize six conifer species with May'97, Jul'97, Sep'97 and Nov'97 hyperspectral data measured at Blodgett Forest Research Station, Department of Environmental Science, Policy and Management, University of California at Berkeley. The experimental results show that, when 6-20 bands were selected from a total of 161 bands, the average identification accuracies of tree species using the new method can be 11.20% higher than those with the method of equal-interval band sampling. The band selection method introduced in this paper is not complete and needs further improvement. In both band selection methods, one developed in this paper and other developed in 1996 (Pu and Gong, 1996), there all exists a shortage to be improved, which is that noise mixed in spectra is not accurately estimated and further removed from spectral signal under considering band selection. We propose to make effort on the de-noise issue to improve band selection method in the future.

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Table 3. Summary of accuracy comparison of species recognition with bands selected by BPPCA 30-eienvector, singular eigenvectors and EIBS.

#band	May'97			Jul'97			Sep'97			Nov'97			Average		
	EIBS	30V	SingV	EIBS	30V	SingV	EIBS	30V	SingV	EIBS	30V	SingV	EIBS	30V	SingV
20	89.6	90.6	90.6	78.1	81.3	82.3	95.8	96.9	89.6	79.2	76.0	79.2	85.7	86.2	85.4
18	95.8	88.5	92.7	74.0	88.5	86.5	81.3	96.9	88.5	74.0	78.1	75.0	81.3	88.0	85.7
16	80.2	87.5	91.7	72.9	82.3	79.2	82.3	93.8	88.5	71.9	80.2	69.8	76.8	86.0	82.3
14	77.1	88.5	87.5	72.9	78.1	79.2	87.5	88.5	87.5	75.0	69.8	64.6	78.1	81.2	79.7
12	77.1	80.2	83.3	69.8	69.8	77.1	70.8	91.7	84.4	60.4	74.0	61.5	69.5	78.9	76.6
10	70.8	78.1	78.1	60.4	68.8	70.8	64.6	91.7	85.4	59.4	61.5	65.6	63.8	75.0	75.0
8	71.9	76.0	71.9	58.3	62.5	55.2	58.3	87.5	81.3	62.5	62.5	71.9	62.8	72.1	70.1
6	51.0	66.7	56.3	54.2	55.2	46.9	52.1	90.6	61.5	54.2	57.3	60.4	52.9	67.5	56.3
Mean	76.7	82.0	81.5	67.6	73.3	72.2	74.1	92.2	83.3	67.1	69.9	68.5	71.4	79.4	76.4

Note: EIBS—equal-interval band selection; 30V—band selection based on the sum of 30 the first thirty eigenvectors; SingV—band selection based on individual eigenvectors (1st three); and underlines indicate the highest accuracy per dated data and per number of band selected.

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