Using Foreground/Background Analysis to Determine Leaf and Canopy Chemistry

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I. INTRODUCTION

Spectral Mixture Analysis (SMA) has become a well established procedure for analyzing imaging spectrometry data, however, the technique is relatively insensitive to minor sources of spectral variation (e.g., discriminating stressed from unstressed vegetation and variations in canopy chemistry). Other statistical approaches have been tried e.g., stepwise multiple linear regression analysis to predict canopy chemistry. Grossman et al. (1994) reported that SMLR is sensitive to measurement error and that the prediction of minor chemical components are not independent of patterns observed in more dominant spectral components like water. Further, they observed that the relationships were strongly dependent on the mode of expressing reflectance (R, –log R) and whether chemistry was expressed on a weight (g/g) or area basis (g/m^2). Thus, alternative multivariate techniques need to be examined. Smith et al. (1994) reported a revised SMA that they termed Foreground / Background Analysis (FBA) that permits directing the analysis along any axis of variance by identifying vectors through the n-dimensional spectral volume orthonormal to each other. Here, we report an application of the FBA technique for the detection of canopy chemistry using a modified form of the analysis.

II. DATA SETS AND METHODS

II.1. The leaf reflectance / chemistry data sets

The study used two datasets representing a wide range of species having divergent foliar adaptations and conditions. These datasets were the LOPEx (Leaf Optical Properties Experiment) obtained from the Joint Research Centre in (Jacquemoud et al., 1994), and a similar but smaller dataset from the Jasper Ridge Biological Preserve at Stanford University (Grossman et al., 1994). The range of variation – several orders of magnitude – depended on the dataset and the specific chemistry (Jacquemoud et al., 1995). Expressing reflectance as -log R or other transforms provides other characteristics of the variance structure that could be better exploited. The variance structure is especially critical for variables like nitrogen that are in low concentration and do not express a wide range of variance between species.

II.2. The analysis

The general form of the SMA equation for each band is expressed as:

$$DN_b = \sum_{em=1}^{Ne} F_{em}.DN_{em,b} + E_b$$, where DN_b is the pixel radiance at band b, F_{em} is the fraction of each endmember DN_{em} weighting their radiance at band b, and E_b is an error term accounting for the unmodeled radiance in band b. Endmembers are chosen to explain the spectrally distinct materials that form the convex hull of the spectral volume. This approach can not minimize the spectral variation of endmembers whose characteristics are unrelated to chemistry detection. A methodology that could cluster this variation into a common point is desired. In response to this problem Smith et al. (1994) divide spectral measurements into groups called "foreground" and "background" spectra. Their FBA approach defines a w vector (with components w_b at each band b) such that all foreground DN spectral vectors are projected to 1 and all background DN vectors to 0. This property is set by the FBA system of equations:

$$\text{foreground} \quad \sum_{b=1}^{N} w_b.DN_b + C = 1 \quad \text{and background} \quad \sum_{b=1}^{N} w_b.DN_b + C = 0 \quad \text{material}$$

where C provides a translation. A singular value decomposition algorithm is used to determine the vector w and the real constant C that optimizes both foreground and background equations simultaneously. This analysis can be extend to a general system of equations in which the projections of each spectra along the vector w are its respective chemistry content. In such a way spectra are discriminated by their relation to chemistry variables. In the singular value decomposition we selected the seven highest eigenvalues and their respective orthonormal eigenvectors to account for the spectral variability.

III. RESULTS

III.1. At leaf level

The FBA was performed to define the best vector for discriminating each chemistry shown in Table 1. The analysis was performed both on the JRC and Jasper Ridge fresh leaf datasets, and on the JRC dry leaf dataset using R, −log R,and other non-standard transformations, like

FUNCTION	CHEMISTRY										
	NITROGEN			CELLULOSE			CARBON			WATER	
DATA	JRC fl	JRC dl	JR	JRC fl	JRC dl	JR	JRC fl	JRC dl	JR	JRC fl	JR
R2	0.69	0.60	0.33	0.38	0.29	0.81	0.40	0.27	0.63	0.94	0.91
R	0.68	0.54	0.31	0.31	0.27	0.79	0.40	0.39	0.71	0.94	0.89
Log(1/R)	0.60	0.34	0.30	0.20	0.22	0.64	0.42	0.39	0.82	0.94	0.87
Filter(R)	0.62	NO	0.32	0.50	NO	0.65	0.44	NO	0.83	0.92	0.90

the squared reflectance (R^2). We calculated the multiple correlation coefficient (r^2), to compare the predicted values to the measured chemical concentrations. The best fit overall (0.94) was found for predicting water content (g/g). These results show that the highest r^2 are found for spectra having high chemical variance (Fig. 1). Low r^2 values correspond to chemistry variables that have limited variance. For example, nitrogen has a wider range of variation in the JRC dataset than the Jasper Ridge dataset and the former has higher r^2. In contrast, cellulose has greater variance in the Jasper Ridge dataset and produces a higher r^2. The best-fit predicted and measured chemistry is shown in Figure 2. These results also show that spectra are dominated by the mean reflectance response (related to albedo) rather than variability due to minor absorptions. Clearly this is undesirable for detection of canopy chemistry. We can try to improve detection by considering additional transformations that reduce the effect of variance around the continuum reflectance and maximize shape differences. Such transformations might improve predictions and provide a better basis for predicting canopy biochemistry of minor constitutents.

The first operation was to normalize the spectra and remove albedo differences,

$$R = \frac{R}{\|R\|} \text{ where } \|R\| = \sqrt{\sum_{i=1}^{N} R_i^2} \text{ denote the norm of the reflectance vector R.}$$

The next step uses the fact that high variance values in any signal (reflectance in our case) has frequency output in the Fourier domain that may be dominated by response to the dc (response at frequency zero). The dc problem can be alleviated in different ways in the Fourier domain. We applied a Discrete Fourier Transform (DFT) to the 211 band spectrum to remove high frequency response (typically related to noise) and a low frequency filter to alleviate the dc response. The effects of these operations are shown in Figure 3. Normalization of the reflectance spectrum does not affect the shape although it does affect the wavelength dependent variance structure. The DFT filtering step clearly changes the shape of the spectrum (mean reflectance information is lost), but enhances other desirable characteristics of the variance structure. The r^2s of the FBA analysis on the normalized DFT dataset are shown in

Table 2. The r^2s of the chemistry variables that have low sample variance (e.g., nitrogen and cellulose) are improved using the squared spectrum, while those with high concentration or having high intra-sample variability (like water) maintain an acceptable level of prediction

III.2. Application to AVIRIS data

The FBA chemistry vectors (water, nitrogen, lignin, and cellulose) derived from the JRC samples were applied to normalized and filtered AVIRIS images of agricultural fields near the city of Davis (CA) and to multitemporal images of Jasper Ridge (CA). These results showed distinct spatial patterns that were related to land cover and land use and with little evidence of random noise. The chemistry patterns were not identical and followed expected patterns for various land cover classes, e.g., high cellulose concentrations occurred in dry grasslands where water contents and nitrogen concentrations were low. Other patterns were generally consistent with ecological characteristics.

IV. CONCLUSIONS

The variance structure of the spectra is highly correlated with biochemical absorptions. Where large variance exists for absorption wavelengths, the relationship to chemistry can be demonstrated. Thus water, for instance, can be estimated by FBA with a high r^2 and a predicted relationship that is close to a 1:1 correlation. Relationships are less satisfactory for chemicals that do not show much intrasample variance or have poorly defined spectral features. However, the r^2 values are improved in datasets where variance has been maximized. These patterns are observed by comparing the nitrogen, cellulose and carbon r^2 between Jasper Ridge and JRC (Table 2). Nitrogen concentration at JRC is about 2 times that at Jasper Ridge while cellulose concentrations are reversed (Grossman et al., 1994). Chemistry predictions for low-variance datasets are improved by normalization and filtering before application of the FBA while these procedures do not significantly affect the prediction of chemistry for samples having a high range of variance.

When FBA vectors are applied to AVIRIS image datasets the results show distinct spatial patterns that follow ecological characteristics. Even biochemicals, like cellulose and carbon, that have low slopes and r^2 (~0.4–0.5) show spatially explicit patterns that follow expected landscape trends. Further, spatial patterns are somewhat independent for each biochemical. Thus, although we lack sufficient field data to adequately validate the image patterns, preliminary results support the possibility of developing direct detection of canopy chemistry using imaging spectrometry.

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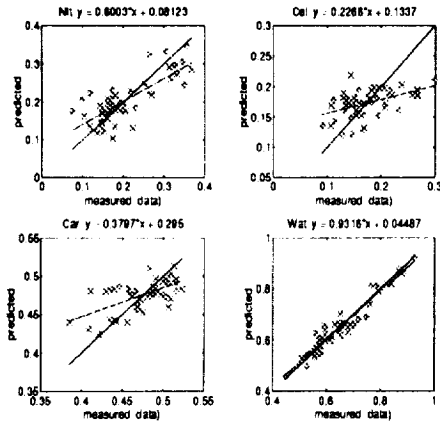
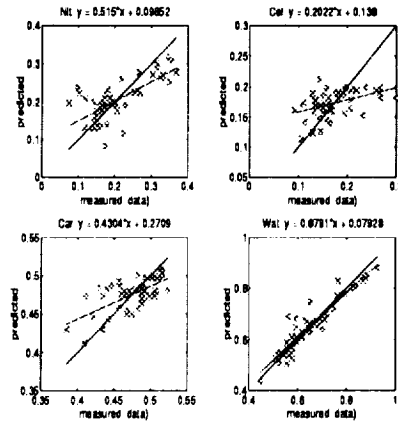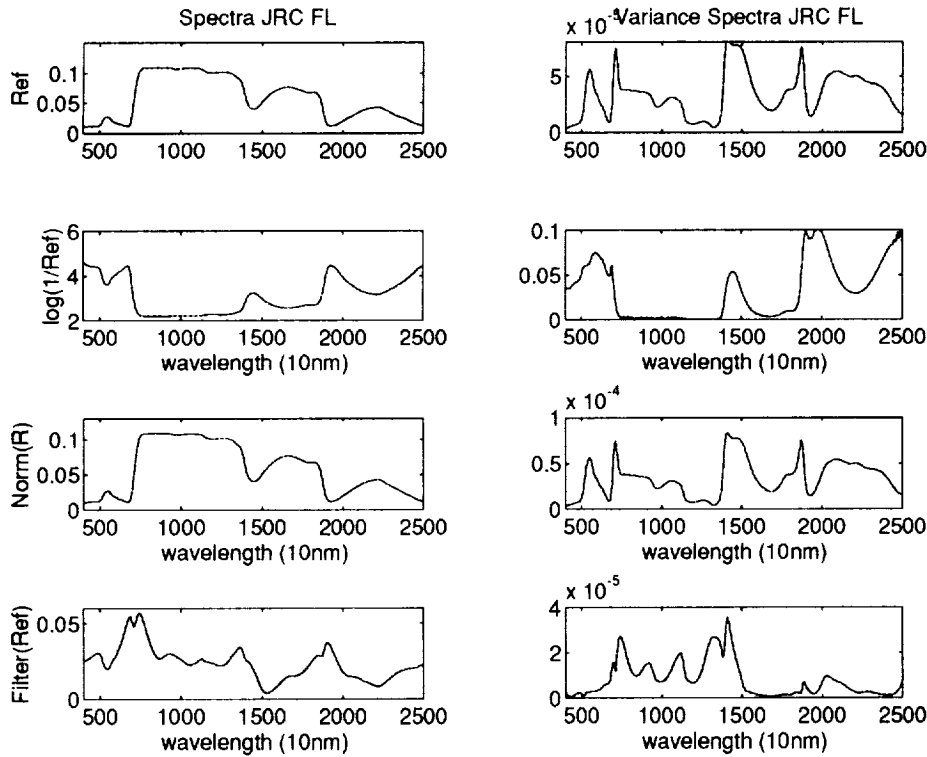Fig. 1. Best fit by standard methods

Fig. 2. Best fit by filtering spectra

Fig. 3. Effects of the transformations for spectra and variance.