© EARSeL and Warsaw University, Warsaw 2005. *Proceedings of 4th EARSeL Workshop on Imaging Spectroscopy. New quality in environmental studies*. Zagajewski B., Sobczak M., Wrzesień M., (eds)

FOREST CLASSIFICATION USING HIGH SPECTRAL AND SPATIAL RESOLUTION DATA

Juho Lumme

Helsinki University of Technology, Department of Surveying, Espoo, Finland; Juho.Lumme@tkk.fi

ABSTRACT

A modern airborne imaging spectrometer provides an exact observation of the object's spectral properties. Besides, the spatial resolution of imaging spectrometers is good and instruments provide information about object texture. Many nature objects can be identified by their characteristic reflection. However, the spectral properties of certain plants are similar and the identification made only by their reflectance spectra does not work. If the texture of different plant classes is distinguishable, we can identify them by using texture analysis.

The purpose of this work is to classify data using both spectral and texture information of hyperspectral image and thereby improve classification results. The goal was to find the best working texture measures and feature sets including both spectral and texture features.

Test area located in Southern Finland was imaged by an airborne imaging spectrometer. The area included mostly coniferous and deciduous forests. Separability measures between each class were calculated using different feature sets. Features included original image channels and new texture measures. Finally the data was classified using Bayesian and neural network classification.

Separability measures calculated from the training data using individual image channels and texture images were poor. Using more spectral features at the same time predictable improves the results. Average separability increased notably and all the classes were able to distinguish from each other when both spectral and texture features were taken for the classification.

Taking texture measures into account in the forest classification was reasonable because forest stands have individual texture and the spatial resolution of the hyperpsectral image was good enough to observe the texture. The methods and results in this study can apply to the satellite case where texture features are calculated from a high resolution satellite sensor and spectral features are calculated from a satellite imaging spectrometer.

INTRODUCTION

Forests are one of Finland's most important natural resources. Over two-thirds of the land area is covered by forest. Finland has efficient forestry and timber is an important export for the country. Besides, forests have biological, social and cultural significance. Therefore, we must assure the diversity and health of forests.

Remote sensing has been recognized as an efficient tool for forest inventory (1). It allows us to observe accurate and up-to-date data from large forest areas. Imaging spectrometers allow the acquisition of images in hundreds of contiguous and very narrow bands. They provide a continuous and exact reflectance spectrum of the observed object. Usually the object can be identified from its characteristic spectral reflectance.

The reflectance spectrum of green vegetation in the visible region is controlled by contribution of chlorophyll. The spectrum in the near infrared region is controlled by water content and the contribution of other organic material. Different plant species usually have characteristic reflectance spectrum. However, it is obvious that water content and contribution of chlorophyll are not constants even in the same kind of plants and it causes variation in reflectance values. Besides, the reflectance values of two different plants are sometimes very similar. This leads to the problem that certain vegetation classes mix together.

When looking at remote sensing images with high spatial resolution, it is possible to distinguish different age forest types. Even if reflectance of different age trees are very similar. This is mainly based on the texture of the forest. Taking texture into consideration we get more information about the forest.

AISA imaging spectrometer data were investigated in this study and the main purpose was to calculate different texture features and combine them with spectral features. Texture measures were calculated using the co-occurrence matrix. Separability measures between forest classes were calculated using several different feature sets to determine feature sets usefulness in forest type classification. Finally, Bayesian and Perceptron neural network classifications were performed using previously selected features.

METHODS

Test area

Aerial measurements with an AISA airborne imaging spectrometer were made at Lammi in Southern Finland. The area contains mainly lakes, rural areas, cultivated fields and coniferous and deciduous forests. Size of the test area was about 50 kilometres long and 2 kilometres wide.

AISA imaging spectrometer data

AISA data was acquired from an aeroplane on September 1999. Six strips were flown and raw data was gathered to the actual hyperspectrum image and geometric correction was performed.

Table 1: Channels of the AISA image

Channel	Wavelength (min)	Wavelength (max)	Channel	Wavelength (min)	Wavelength (max)
1	448.99	456.27	10	667.46	675.05
2	470.84	478.13	11	696.32	703.91
3	491.24	498.53	12	744.93	752.52
4	520.38	527.67	13	776.83	784.42
5	548.06	555.35	14	796.57	804.17
6	572.83	580.12	15	840.62	848.22
7	597.60	604.89	16	857.33	864.93
8	620.91	628.20	17	866.45	874.04
9	644.67	652.27			

Figure 1: An example of AISA data. (Image: Geological Survey of Finland)

Finnish Forest Research Institute preprocessed the data. The pixel size of the image was 1.1 meter. Image contained 17 visible and near infrared channels. The weather took a turn for the worse during the flight and the illumination was low in last strips.

Field surveys

Geological Survey of Finland did all the fieldworks in 1999 and 2000. Training area inventory included over 250 training areas. For example, the primary sources of reflection, the vegetation and the soil class were specified in field inventory.

Preliminary works

The Finnish Forest Research Institute performed the preparation and correction of the AISA data. Geometric correction utilizes location and attitude information of differential GPS and gyro. Besides, operator adjusts ground control and tie points to refine the geometric accuracy. The raw data numbers were converted to physical units of radiance using calibration targets (2).

In this study, we were only interested in forests. First, we used NDVI to separate vegetation from other ground features and then the forest was separated from other vegetation types like cultivated fields. This was done based on image texture. Next, the forest mask was filtered using mode filtering to remove tiny areas. In the end, we get mask that represents forest areas and all farther analysis was performed inside the mask.

Feature extraction

Principal component analysis was applied to the spectral channels and tree first principal component channels were stored. Besides, NDVI vegetation index was calculated using red and near infrared channels.

Texture measures were computed from the first principal component channel. At first, tree different window sizes (25, 35 and 45 pixels) and distances between the pair of pixels (1,3 and 5 pixels) were used for produsing the co-occurence matrices (3). Next, several different texture measures were computed from the co-occurence matrices:

1. Homogeneity,
2. Contrast,
3. Dissimilarity,
4. Mean,
5. Standard Deviation,
6. Entropy,
7. Angular Second Moment,
8. Correlation and
9. Inverse Difference.

Altogether we got 81 different texture features. Some texture measures did not seem to work properly and they were ignored in later studies.

RESULTS

Separability measures - individual features

Forest classes in this study were birch, spruce and pine. Besides, these classes were divided into subclasses according to the age of the forest (seedling, young plant and old plant). Separability measures between each class were calculated using the Bhattacharya Distance (4). Table 1 shows average separability of 17 image channels, 3 principal component channels and 6 texture features. More separability measures were computed using texture features but only the best results were shown. The values of window size and distance between the pair of pixels is also included in the table although theirs effects were rather small in this case.

Table 2: Average separabilities of the classes in the case of different features: 0 < x < 1 (very poor separability); 1 < x < 1.9 (poor separability); 1.9 < x < 2 (good separability).

Channel	Average separability	Channel	Average separability		
1	0.25	14	0.48		
2	0.31	15	0.47		
3	0.37	16	0.46		
4	0.45	17	0.45		
5	0.43	1. PCA	0.51		
6	0.52	2. PCA	0.34		
7	0.60	3. PCA	0.11	Window & distance	
8	0.63	Homogeneity	0.58	25x25	5
9	0.65	Contrast	0.49	35x35	1
10	0.64	Dissimilarity	0.52	35x35	3
11	0.61	Mean	1.19	25x25	5
12	0.36	Entropy	0.57	25x25	1
13	0.45	Inverse Difference	0.56	25x25	3

Class separation was poor when only individual features are used. Red light channels gave the best separability results in the visible and near infrared region. The birch stands were easily separated from the spruce and pine stands in all age classes. Unfortunately, the spruce and pine stands were mixed together and also forest types of different age were mixed.

When talking about texture features, we got the best separability results using Mean texture measure. Almost all class combinations were distinguished better when Mean texture measure was used. However, there were still classes that mixed together. For example, old spruce and pine stands and young spruce and birch were mixed.

Separability measures – feature sets

Now, the separability measures are defined so that several features are used together at the same time. Both the spectral and the texture features are used. Besides, the principal component and NDVI features were used.

The best set of channels was selected using algorithm that is based on the divergence of the class signatures. The results were three channels in the red light and near infrared wavelength region. Table 2 shows the average separability of four different feature sets. The first include three original image channels. The second include three channels obtained by using principal component analysis and the third feature set includes three texture features. Finally, all these features were included in the last feature set.

Table 3: Average separabilities of the classes in the case of feature sets: 0 < x < 1 (very poor separability); 1 < x < 1.9 (poor separability); 1.9 < x < 2 (good separability).

Feature sets	Average separability
Channels: 9, 11, 13	1.36
Principal component channels: 1, 2, 3	1.04
Texture measures: Contrast, Dissimilarity, Mean	1.63
Channels: 9, 11, 13; principal component channels: 1, 2, 3; NDVI channel; Texture measures: Contrast, Dissimilarity, Mean	1.93

Separability measure results were significantly better when using feature sets instead of individual features and when both spectral and texture features were used, all the classes were easily distinguished. In practise, some seedling stands mixed. The problem was that there was not enough training data about seedlings.

Image classification

Image classification was made using Bayes and Perceptron neural network algorithms. The area was classified into the following different forest types: birch (seedling), birch (young/old), spruce (seedling), spruce (young), spruce (old), pine (young) and pine (old).

The classification was performed using several different feature sets. The first Bayes classification was performed using three principal component channels and the second classification was performed using three additional texture features. Finally, we also added three original channels and NDVI channel and performed the third classification. Perceptron neural network classification was performed using all the 17 original channels and six texture features.

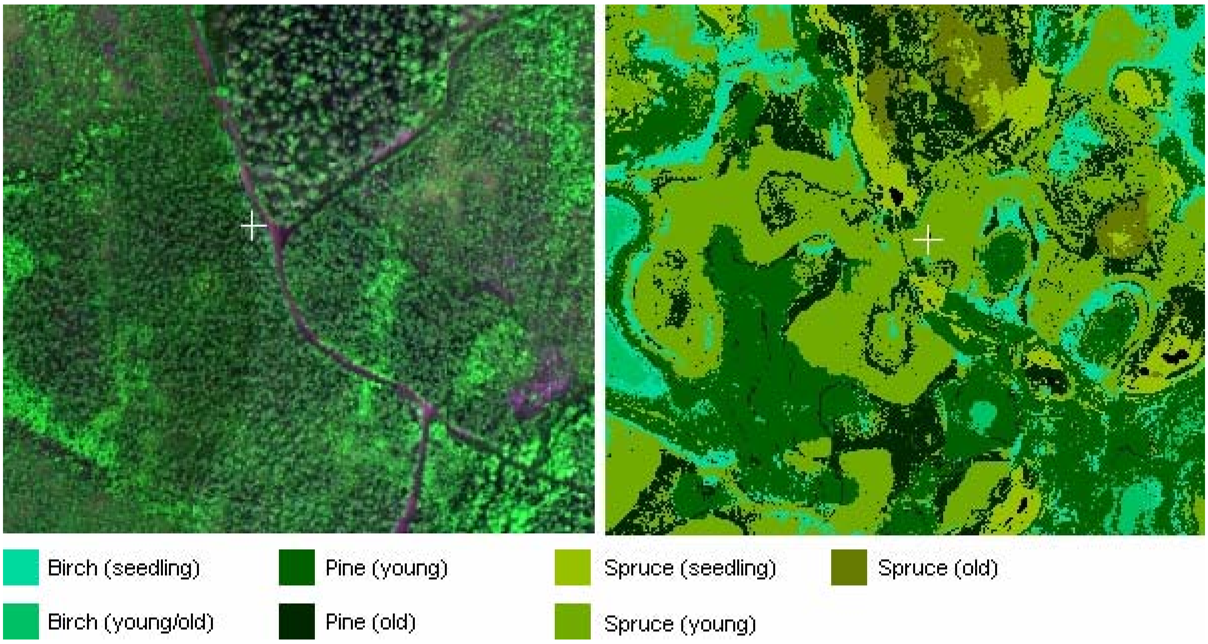

Figure 2: A piece of the original image and classification results of the Perceptron neural network classification algorithm.

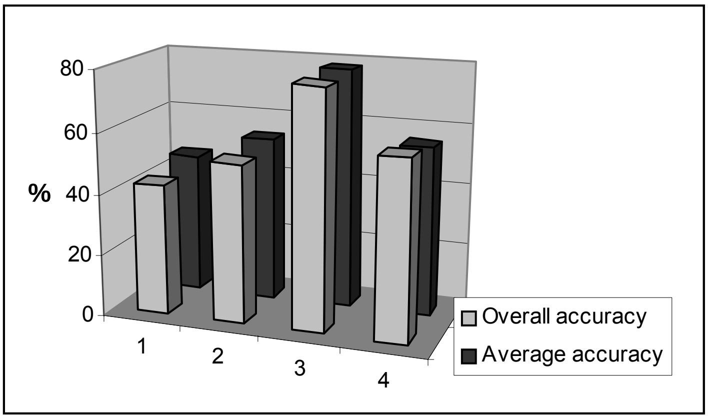

Figure 3: The average and overall accuracies of the Bayes and Perceptron neural network classifications. 1 = Bayes classification with principal component channels. 2 = Bayes classification with principal component channels and texture features. 3 = Bayes classification with three original image channels, principal component channels, NDVI and texture features. 4 = Neural network classification with all original image channels and texture features.

Average and overall accuracies were calculated (Figure 3). The average accuracy is the average of the accuracies for each class. Overall accuracy is a similar average with the accuracy weighted by the proportion of test samples. The Bayes algorithm led to better results when both the texture and spectral features were used. Neural network did not performed as well. Old pine class usually mixed with the spruce class and the results of the seedling classes were rather uncertain in both classification methods.

CONCLUSIONS

The classification accuracies were moderate but we must remember that often these forest classes were spectrally similar and the forest texture varied inside the classes. Including more training data and spending more time on feature extraction we probably could have better results. However, this case has shown that it is worth including both spectral and texture features on forest airborne hyperspectral data analysis.

The results of this study are able to generalize to the case in which the data is obtained from satellites. It means that we must combine two different satellite images. Using high spectral resolution satellites we get the spectral features. To measure forest texture we need data with better spatial resolution. At present, we can get panchromatic satellite images at less than a meter resolution, which is good enough to detect the forest texture.

References

1 E Tomppo, 1991. Satellite image-based national forest inventory of Finland. International Archives of Photogrammetry and Remote Sensing, 28: 419-424.

2 Mäkisara K, A Lohi & J Kärnä, 1994. A system for geometric and radiometric correction of airborne imaging spectrometer data. In: International Geoscience and Remote Sensing Symposium, edited by T Stein, 851-853.

3 Haralick R, K Shanmugan & I Dinstein, 1973. Textural features for image classification. In: IEEE Transactions on Systems, Man and Cybernetics, 3(6), 610-621.

4 J Richards, 1986. Remote Sensing Digital Image Analysis (Springer-Verlag) 281 pp.