Forest Classification Using Spectrometer and SAR Data

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Abstract
This work deals with automatic classification of forest areas using remote sensing imagery. We compare the discrimination ability of two complementary sensors, a SAR sensor and a spectrometer. A Gaussian maximum likelihood classifier was used in all classification experiments. The hyperspectral data alone gave fairly good results for classification of tree species. The results for SAR data alone were not convincing. Joining the two data set in a simple fusion experiment improved the results obtained significantly for data from a single sensor, and also allowed a classification of tree species and height simultaneously.

INTRODUCTION

Forest inventory on a local scale is today heavily depending on expensive ground measurements. Use of remote sensing has started to reduce this costs, and has a potential for reducing them further dramatically. Several studies have been done on the capability of SAR images to retrieve biophysical characteristics of the forest [3], [7], whereas others have investigated the potential of optical sensors for the same purpose [1], [2]. The most promising in the last category are imaging spectrometers.

This work aims first at demonstrating the capability of an imaging spectrometer to discriminate tree species, and its superiority to more traditional optical sensors for this purpose. The second goal is to compare the results obtained on the hyperspectral image to those obtained for SAR images on the same site. Finally, this work investigates the potential of data fusion: Will the multisensor classification of the hyperspectral image and the SAR images give better results than using only one of the two?

THE DATA SET

The test site is located in France, in the Fontainebleau forest south of Paris and contains oak, beech and pine trees in a relatively flat area. The data consist of field measurements, airborne spectrometer images, and airborne SAR images. The flights and the ground data collection took place during the European EMAC campaign in 1994.

Field Data

For each forest stand the tree species and the quantitative mean characteristics in table 1 were available.

Spectrometer Data

In this project, we use data acquired with the german airborne Reflective Optics Spectrometric Imaging System (ROSIS) in the frame of the European Multisensors Airborne Campaign (EMAC-94). The data from May 10th 1994 are investigated in this study. It was flown at 10,000 m altitude. The data were calibrated and roll corrected, but not atmospherically corrected. They consist of 81 spectral bands in the visible and near-infrared spectrum. The spectral sampling varies from 12 nm in the lower part of the spectrum to 4 nm in the upper part. The images have been resampled from the original $16 \times 16 m^2$ resolution to $5.6 \times 5.6 m^2$.

SAR Data

The 10 SAR images were acquired with the E-SAR sensor during three campaigns from April to June. They cover the X (3cm wavelength) and P (65cm) bands with HH polarization, and C (6cm)and L (24cm) bands with both HH and VV polarization. The original resolution was $4 \times 10 m^2$ (P-band) and $4 \times 3 m^2$ (other bands). The images were first speckle filtered using a Gamma Map filter, then normalized to 45 degrees incidence angle using a cosine correction method, before being co-registered with the hyperspectral image.

DATA ANALYSIS

Hyperspectral

After some preliminary investigation we decided to divide the forest into six classes, based on type and tree height: oak 1 (0-13m), oak 2 (13-30m), oak 3 (30m-), beech 2 (13-30m), beech 3 (30m-), pine. There were also some forest stands with mixed deciduous trees. These were omitted from our study, since we have no ground truth information about the relative portions of the various tree species within each stand. For the purpose of classification based on the ROSIS spectrometer we consider four classes: oak 1 (0-13m), oak 2+3 (13m-), beech, pine.

After dividing the data into a training set and a test set, we computed the mean spectra from the training set, see Fig.1.

From Fig.1 we see that atmospheric features appears. These features are due to absorption, of O_2 at 762nm and of H_2O at 720nm and 820nm.

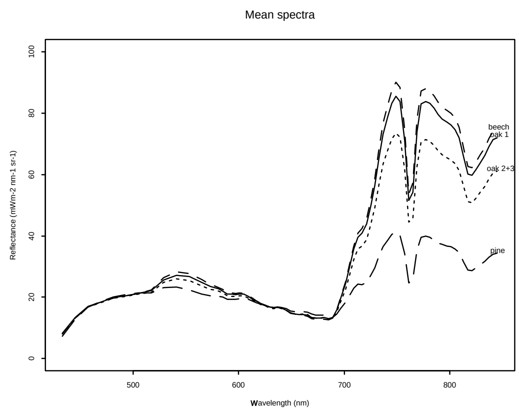

Figure 1: *Mean spectra for the hyperspectral image*

Previously, only a small number of spectral bands have been available. Therefore, we want to classify the forest using a small subset of the available spectral bands for the purpose of comparison. It appears that most of the discriminatory information is contained in the upper part of the spectrum.

The bands should be selected in order to maximize the Bhattacharyya distance, [4], between pair of classes. Since there are several pairs we maximize the estimated average Bhattacharyya distance. Since the number of all possible feature combinations is very large an exhaustive search is prohibitive. Therefore we use a suboptimal approach called sequential forward selection, [4].

SAR

Tree Species

The same 4 classes as for the spectrometer data were used for tree species/height classification. Although the E-SAR images cover a larger area than the ROSIS image, and therefore might exploit more of the field data, the same training and test data set was used as for the ROSIS image. This was to ensure a fair comparison of classification results from the two data set, and to facilitate the multisensor classification experiment. Mean backscatter values for each of the 4 classes and for the 10 different frequency-polarization images are shown in Fig.2. Image

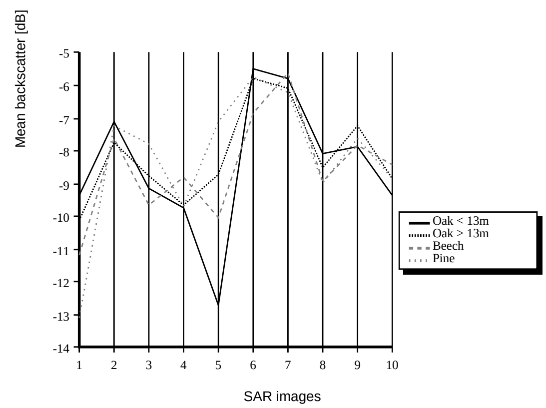

Figure 2: *Mean values for each class for the 10 SAR images*

number 5, P-band with HH-polarization, looks the most promising. However, the standard deviations of the values vary between 1.4 and 4.0 dB, and for each of the images at least two classes are separated by less than a standard deviation. This means that first order statistics will certainly not be sufficient to distinguish between the four classes.

The Bhattacharyya, or Jeffries-Matusita, distance was utilized to estimate the mean and minimum class separability for each of the 10 images. Best separability was obtained when using all 10 images simultaneously. This was also the case for the hyperspectral and is in accordance with theory [5].

Biomass

Due to the low number of biomass data, which consist of the mean value for each forest stand, data not covered by the hyperspectral image were also used in this study. Plots for each image of the mean backscatter value within each forest stand versus its mean biomass indicate that the estimation of biomass using only one image is extremely difficult. Fig.3 shows the most promising plot, which is for the P-band. Clearly, no regression is possible for all forest stands. However, several experiments trying to find a regression model between forest biomass and backscatter values found a saturation of the latter at a level depending on the frequency band. The longer the wavelength, the higher the saturation point. For P-band the saturation level has been reported between 150 and 250 tons/ha. Also it has been reported that relation between biomass and backscatter depends on forest structure [3]. Stands dominated by a different tree species should consequently be treated a part. Considering only oak stands in Fig.3 a linear or other relation for the lower biomasses with a saturation level between 150 and 225 tons/ha seems plausible. The same could be the case for pine stands, but only 4 values below 200 tons/ha do not provide a sufficient data set. For the beech stands, no regression model would fit.

The best results were obtained for a linear regression for oak below 200 tons/ha which gives a coefficient of determination of 0.83, and for a loglinear regression for all oak stands which gives a coefficient of determination of 0.80. This last result is in accordance with the results obtained by Proisy et al. [6].

Using multiple regression would probably ameliorate the results for stands other than oak below 200 tons/ha, but the ground truth data set does not provide sufficient statistics.

As a consequence, to be able to extract useful information about biomass from every pixel, a regression model is not suited for these data.

An alternative approach is to define biomass classes and try to classify each pixel into one of these classes. For this, 5 biomass classes were defined (units are tons/ha): 1: 0-75, 2: 75-175, 3: 175-275, 4: 275-375 and 5: above 375. A similar analysis to the one for species classification was performed. The best separability was obtained for the set of all 10 bands.

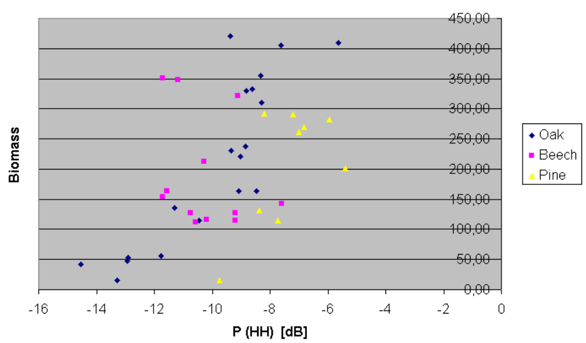

Figure 3: *Biomass versus backscatter for the P-band Sar image*

CLASSIFICATION

A *Gaussian Maximum Likelihood* (GML) classifier is used in all classification experiments. For comparison we also test the *Minimum Euclidean Distance* (MED) classifier on the hyperspectral data.

Hyperspectral classification

The mean percent correct classification rates for the various number of features when the *Gaussian maximum likelihood* classifier is used are visualized in Fig.4. We see that the classification accuracy increases as the number of features increases. The highest correct classification rate is 85.5%.

However, if the *Minimum Euclidean Distance* classifier is used, increasing the number of features does not improve the classification accuracy. Then the correct classification rate does not exceed 57%.

Confusion matrix for the case where all the 81 bands are used, are shown in Table 2. We see that *pine* is relatively easily distinguished from the three other classes. The correct classification rate is higher than 80% for each class.

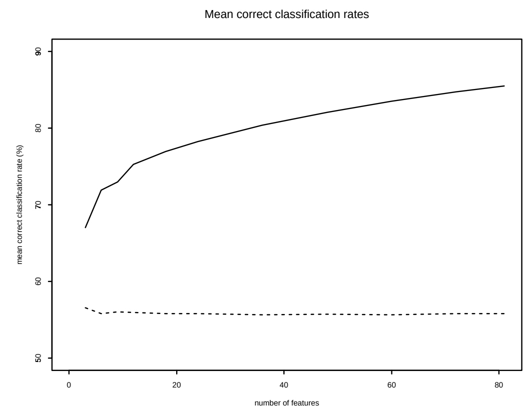

Figure 4: *Classification rates*

Band Averaging

In order to demonstrate the usefulness of the hyperspectral imagery for classification of forest we produce images similar to images acquired by known sensors, such as Landsat TM, SPOT and airborne IR-film camera. These sensors have a small number of spectral bands. Each band of these images is produced by averaging the ROSIS bands with wavelength within its spectral range corresponding to one of the spectral bands of a given sensor. Table 3 shows the spectral range of the bands of interest. Note that there is no ROSIS band corresponding to wavelengths longer than 850 nm. Moreover, the IFOV of the ROSIS sensor is not the same as the IFOV of the other sensors. Thus the comparison may not be adequate.

The images corresponding to each sensor were classified using the Gaussian Maximum likelihood classifier. Table 4 shows a summary of the results. The table suggests that we may obtain 65.3% mean percent correct classification rate using Landsat TM while Spot and airborne film camera yield slightly worse results. Since we obtained 85.5% using hyperspectral methods we believe that remote sensing spectrometry has a greater potential than traditional imagery for forest classification.

SAR classification

	# of stands	Biomass (tons/ha)	Height (m)	Stem density (N/ha)	Diameter (cm)	Basal area (m2/ha)
Oak	19	15-420	5-41	33-17525	2.5-62	3-28
Beech	12	111-351	14-33	413-5053	6-18	10-17
Pine	8	115-292	21-26	86-1304	16-43	12-30
Mixed	5	140-361	24-38	89-1025	12-40	10-18

Table 1: Characteristics and range values available for the stands covered by the spectrometer image and the SAR images.

	Classified			
True	oak 1	oak 2+3	beech	pine
oak 1	80.8	12.6	6.3	0.3
oak 2+3	7.3	83.7	7.8	1.2
beech	6.9	11.8	81.1	0.3
pine	1.0	1.9	0.5	96.5

Table 2: The table summarizes the classification results in the case where 81 bands and the Gaussian Maximum likelihood classifier were used. The element in row i and column j contains the mean percent of pixels of true class i classified as class j.

Sensor	Band number	Spectral range of band (nm)	Spectral range of ROSIS bands (nm)
Landsat TM	1	450-520	457-517
	2	520-600	529-597
	3	630-690	633-689
	4	760-900	761-845
SPOT	1	500-590	505-589
	2	610-680	601-677
	3	790-890	793-845
Film	1	525-580	529-577
	2	580-680	581-677
	3	680-900	681-845

Table 3: Spectral bands of known sensors and corresponding ROSIS bands.

Sensor	Number of bands	Mean % correct %
Landsat TM	4	65.3
SPOT	3	64.3
Film	3	64.6
Rosis	81	85.5

Table 4: Mean percent correct classification rates for various simulated imagery. The rightmost column show the percent of correct classification when the Gaussian maximum likelihood method was used.

The GML classifier was also used to classify the SAR images. As predicted by the separability analysis, the classification accuracy is low. For the 4 class tree species/height classification, the ratio X/P is the best 1D-feature and gives an accuracy of 51.3%. The highest accuracy is obtained for the set of all 10 images: 67.5%. This is poorer than the results reported by Rignot et al. [7] who used fully polarimetric C, L and P-band SAR to classify forest types in Alaska. One reason for this might be that there were no cross-polarization images in our data set. Rignot et al. found HV-polarization to be the most useful for all frequencies.

Classifying the images into 5 biomass classes gave an accuracy of 52.0% when using all 10 images, and only 33.4% for P-band which was the best single image. As discussed under the data analysis section, the backscatter reaches a saturation level for a biomass of 150 to 250 tons/ha for the P-band (and even lower for the other bands) and most of the pixels used to estimate the accuracy belong to areas with biomass above that level. This obviously affects the results. Also, according to other works, cross-polarization images might have given better results [3].

Fusion

The simplest and most popular multisensor classification method is the augmented vector approach, which consists in concatenating the data from the different sensors as if they were measurements from one single sensor. This approach allow us to apply the same GML classifier to the joined data set. Of course, the multivariate normal distribution is not theoretically valid here, since we have images from different dates and from sensors which measures completely different physical properties. However the purpose was not to find the best possible fusion method, but to investigate if the use of the joint data set may give significantly better classification results.

For the 4 class tree species/height classification the results are shown in table 5. The classification accuracy is 90.8%. Compared to the accuracy of 85.5% obtained for the hyperspectral image alone, this shows that adding the SAR data improves significantly the classification results.

	Classified			
True	oak 1	oak 2+3	beech	pine
oak 1	90.1	6.5	3.3	0.1
oak 2+3	3.7	89.0	6.5	0.7
beech	4.2	9.1	86.4	0.2
pine	0.1	1.6	0.8	97.5

Table 5: Classification results obtained by using all 81 bands of the hyperspectral image and all 10 SAR images.

The same biomass classification experiment as for SAR data only was also performed with the joined data set. The accuracy obtained was 79.2%, compared to 52.0% for only the SAR images.

Because of these encouraging results, a classification experiment using the original 6 tree species/height classes was also undertaken. These 6 classes had been merged to 4 because of the poor separability using the hyperspectral image alone. Using the joined data set we obtained a classification accuracy of 86.9% (see table 6).

	Classified					
	Oak			Beech		Pine
True	1	2	3	2	3	
oak 1	86.2	2.3	5.9	3.2	2.3	0.1
oak 2	2.5	82.2	9.5	3.2	2.2	0.4
oak 3	2.1	9.3	82.1	3.8	2.1	0.5
beech 2	4.1	3.7	5.8	81.9	4.3	0.3
beech 3	0.3	2.6	3.1	2.8	91.1	0.1
pine	0.1	1.1	0.8	0.2	0.1	97.6

Table 6: Classification results in the case where all 81 bands of the hyperspectral image and all 10 SAR images were classified to 6 species and height classes.

CONCLUSION

We have compared the discrimination ability for forest classification of two complementary sensors, a SAR sensor and a spectrometer. A Gaussian maximum likelihood classifier was used in all classification experiments. The hyperspectral data alone gave fairly good results for tree species classification. A simulated comparison with SPOT, Landsat TM and photographic film shows that the hyperspectral image gives much better results. The results for SAR data alone were not convincing. Joining the two data set in a simple fusion experiment improved significantly the results obtained for data from a single sensor, and also allowed a classification of tree species and height simultaneously.

According to the ground truth data that were used, the forest stands are completely homogeneous. Within for example an oak stand of biomass 50 tons/ha, there should not be a single beech tree, and the biomass should be the same for all 5.6x5.6 m2 squares corresponding to a pixel. This is probably not the case. Also this means that the classification results would certainly have been further improved if a contextual method was used, i.e. by modelizing the a priori probabilities using a Markov Random Field in order to obtain larger and smoother class regions.

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