The VHR data region-based classification possibilities in the framework of Control with Remote Sensing of European CAP.

A. Carleer [a, *], E. Wolff [a]

[a] Institut de Gestion de l'Environnement et d'Aménagement du Territoire, Université Libre de Bruxelles, cp 130/02, 50 av. F.D. Roosevelt, 1050 Brussels, Belgium – (acarleer, ewolff)@ulb.ac.be

Abstract - In the European CAP (Common Agricultural Policy) framework, the European Commission imposes on member states to prevent agricultural subsidy irregularities, and recommends the control with remote sensing (CwRS). In the framework of remote sensing procedure, the European Commission, by the way of his Joint Research Centre, advises the use of very high spatial resolution (VHR) satellite data. These data are extraordinary from the point of view of the spatial resolution but the use of these kinds of data involves some problems in the traditional per-pixel classification like the salt and pepper effect, the poor spectral resolution of the VHR data and the difficulty in classifying land use. The region-based classification could solve these problems and allows the use of other features on top of spectral features in the classification process. This study present the possibility of the VHR data region-based classification to the classification of the agricultural and rural land cover in the framework of the remote sensing control of the European Union CAP.

1. INTRODUCTION

Since 1993, the European Commission DG Agriculture has promoted the use of "Control with remote Sensing" (CwRS) as appropriate control system within the Common Agricultural Policy (CAP) to prevent agricultural subsidy irregularities (Astrand et al., 2004). Since 1999, the MARS (Monitoring Agriculture with Remote Sensing) project at the JRC (Joint Research Centre) centralizes the satellite images acquisition and since a few years, advises the use of very high spatial resolution (VHR) satellite data in the control process. These data are extraordinary from the point of view of the spatial resolution and the gap between the spatial resolution of aerial photographs and satellite images strongly decreased (Carleer and Wolff, 2004), they have the advantages of the satellite images: ability to cover large areas on a routine basis and their large archives. Moreover, these data fulfill the accuracy imposed by the Commission to digitalize the agricultural parcels for the LPIS (Land Parcel Identification System) and can be used for the CwRS at the same time. In the 2004 campaign, for the VHR satellite acquisition there were 71 VHR sites covering 50000 km², for a total number of 221 sites through Europe (Astrand et al., 2004)..

In spite of these advantages, the use of this kind of data involves some problems in the traditional per-pixel classification. With the spatial resolution refinement, the internal variability within homogenous land cover units increases (Woodcock and Stralher, 1987, Alpin et al., 1997, Thomas et al., 2003). The increased variability decreases the statistical separability of land cover classes in the spectral data space and this decreased separability tends to reduce per pixel classification accuracies.

Another disadvantage with the very high spatial resolution satellite images is the relatively poor spectral resolution (Herold et al., 2003).

To overcome these problems, a region based procedure can be used (De Wit and Clevers, 2004, Carleer et al., 2005). The segmentation, before classification, produces regions which are more homogeneous in themselves than with nearby regions and represent discrete objects or areas in the image. Each image region then becomes a unit analysis and makes it possible to avoid much of the structural clutter.

The segmentation has other advantages; it allows measuring and using a number of features, on top of spectral features (Herold et al., 2002a, 2003, Thomas et al., 2003). These features can be the surface, the perimeter, the compactness (area/perimeter²), the degree and kind of texture (Johnsson, 1994). The segmentation is one of the only method which ensures to measure the morphological features (surface, perimeter, shape…) (Segl and Kaufmann, 2001) which may be especially useful when very high spatial resolution data are available (Jensen and Cowen, 1999). The use of these additional features could allow to compensate for the low spectral resolution of VHR satellite images (Guindon, 2000, Herold et al., 2002b) and to increase the classification accuracy for spectrally heterogeneous classes (Lillesand and Kiefer, 1994).

2. OBJECTIVE

The features calculated on the regions can be numerous and they all cannot be used. Using all of them not only makes computer system slow, but compromises the accuracy of the classification (Penaloza and Welch, 1996, Guindon, 2000). A selection of relevant features for each class is then essential to minimize the redundant signatures. This study present a feature selection procedure used in order to show which features (spectral, textural and morphological) are useful for which classes.

Moreover the segmentation technique used in this study makes it possible to segment the image on several levels. Then, this study also ensures to show in which segmentation level the classes are well identified and with which features.

3. STUDY AREA AND IMAGE DATA

The study area is situated at 33 km in the south-east of Brussels (Belgium) and covers a large rural area principally characterized by croplands and pasture lands, but also by roads, isolated buildings, rivers, water bodies and villages. The image data are ortho-rectified SPOT and Ikonos images, acquired on March 17, 2004 and June 7, 2004, respectively.

* Corresponding author.

The data cover a surface of 74 km² and the spatial resolutions are 20 m for the MIR SPOT band, 10 m for the green, red and NIR SPOT bands, 4 m for the blue, green, red and NIR Ikonos bands and 1 m for the panchromatic Ikonos band.

4. METHOD

4.1 Segmentation

The segmentation technique used in this study is a "Region Growing" technique implemented in the eCognition software developed by Definiens Imaging (Definiens Imaging, 2004). The procedure starts at each point in the image with one-pixel objects and in numerous subsequent steps smaller image objects are merged into bigger ones, throughout a pair-wise clustering process. This segmentation technique makes it possible to segment the image on several levels. Each level is made up of the merger of the lower level regions. In this study, 12 different levels were carried out on the basis of two different sets of Ikonos bands (only PAN, and mustispectral bands + PAN). Only the Ikonos bands were used, because we wanted to keep the maximum accuracy for the boundaries location.

4.2 Legend

The land cover legend used in this study is a hierarchical legend with two main classes (Table 1). They subdivided into 17 land cover mainly based on land cover colors and vegetation types or crops (level 2). The three grey levels, the very reflective surface and the red surface are further divided according to intra-class land use (level 3): transportation area and building.

Table 1. Legend

Level 1		Level 2		Level3
vegetation	1	shadow on vegetation	11	
		shrub and tree	12	
		herb (permanent meadow or pasture)	13	
		sugar beet	14	
		potato	15	
		ensilage maize	16	
		winter wheat	17	
		winter barley	18	
		chicory	19	
		textile flax	20	
non-vegetation	2	shadow on non-vegetation	21	
		water	22	
		red surface	23	transportation area **301**
		very reflective surface	24	
		light grey	25	building **302**
		medium grey	26	
		dark grey	27	

4.3 Features

Forty-seven features were calculated on each region of each level for each class. These features can be distributed in three categories: the spectral, textural and morphological features. The spectral features contain the mean of the 9 spectral bands, the mean of Ikonos and SPOT NDVI, and 4 ratios of Ikonos bands. The textural features contain the Standard Deviation of all bands and NDVI, and five Haralick textural features calculated on the PAN and NIR Ikonos band, and on the NIR SPOT band (Homogeneity, Contrast, Dissimilarity, Entropy and Angular Second Moment) (Haralick et al, 1973). The morphological features contain the area, length, width, length/width, perimeter and compactness of the regions.

4.4 Feature selection

In order to find the most suitable features for each class at each segmentation level, the public domain program "Multispec" was used. This program was designed for the analysis of multispectral and hyperspectral image data. The most suitable features are found by calculation of class separability based on the Bhattacharyya distance. The Bhattacharyya distance is defined as:

$$B=\left[M_1-M_2\right]^T\left[\frac{\Sigma_1+\Sigma_2}{2}\right]^{-1}\left[M_1-M_2\right]+\frac{1}{2}\mathrm{Ln}\frac{\left|\frac{1}{2}\left[\Sigma_1+\Sigma_2\right]\right|}{\sqrt{|\Sigma_1||\Sigma_2|}},\quad(1)$$

where μ_i and Σ_i are the mean vector and the covariance matrix of class i, respectively.

The Bhattacharyya distance is a sum where the first part represents the mean difference component and the second part the covariance difference component. A general problem results from having no defined thresholds in terms of class separability. However, this measure can be used to assess separability of land cover classes and to prioritize features that contribute most to discrimination among the land cover classes of interest (*Herold et al., 2003*). The Bhattacharyya distance provides a separability score between each land cover class for a given set of features. This information can be used to identify the features that contribute the largest amount of separation of these classes. The Bhattacharyya distance measure is derived from training areas selected in each level for each class. These training areas were selected by an expert on each segmentation level, as it is commonly done.

The top 5 feature combinations for best average separability are calculated for a combination of four features, for each level of the legend, on each level of the segmentation.

5. FEATURE SELECTION RESULTS

Before beginning the tests on the classes of the different legend levels, we noticed that some crop classes were not covered by vegetation at the two dates (sugar beet, potato, ensilage maize and chicory). Then, we decided to carry out the test with all the legend level 2 classes in order to see the distribution of the classes.

5.1 Discrimination of all legend level 2 classes

The best average separabilies were found with the segmentation level 5 of the Ikonos multispectral and PAN bands. The most relevant features are the mean of the red, NIR and NDVI Ikonos bands and the standard deviation of the Ikonos NDVI.

The results show a special distribution of the classes in the Table 3 (bold frame). Three groups can be defined: the group 1 with the vegetation classes (shadow on vegetation, shrub and tree, herb, winter wheat, winter barley and textile flax), the group 2 with the non covered vegetation classes by crop (sugar beet, potato, ensilage maize and chicory) and the group three with all the non-vegetated classes.
After this test, the legend level 1 changed and the discrimination between the three groups was tested.

5.2 Discrimination of the legend level 1 classes (the three groups)

In this test, the separability is calculated between the three groups called: vegetation, non covered crop, and non-vegetation, respectively. The best average separabilities were found with the segmentation level 4 of the Ikonos PAN bands. The most relevant features are the mean of the Ikonos NDVI the Standard deviation of the Ikonos NIR band and NDVI, and the Angular second moment of the Ikonos NIR band.
The presence of the Ikonos NDVI is not surprising; it is very often used for the identification of the vegetation compared with the non-vegetation.

5.3 Discrimination of the legend level 2 vegetation classes (G1)

In this test, the separability is calculated between the shadow on vegetation, shrub and tree, herb, winter wheat, winter barley and textile flax classes. The best average separabilities were found with the segmentation level 5 of the PAN Ikonos bands. The most relevant features are the mean of Ikonos NIR band, the mean of the SPOT green and NIR bands, and the Standard deviation of the Ikonos NIR band.
There are almost only spectral features, but from two dates. The multi-temporal spectral features are more effective than the spatial features, calculated thanks to the segmentation (textural and morphological features), for the discrimination of the vegetation classes and above all for the crop classes.

5.4 Discrimination of the legend level 2 non covered crop classes (G2)

In this test, the separability is calculated between the sugar beet, potato, ensilage maize and chicory classes. The best average separabilities were found with the segmentation level 1 of the PAN Ikonos bands. The most relevant features are the mean of Ikonos red, NIR and NDVI band, and the Angular second moment of the Ikonos NIR band.
There are almost only spectral features from only one date.

5.5 Discrimination of the legend level 2 non-vegetation classes (G3)

In this test, the separability is calculated between the shadow on non-vegetation, water, red surface, very reflective surface, light grey, medium grey, dark grey classes. The best average separabilities were found with the segmentation level 2 of the multispectral and PAN Ikonos bands. The most relevant features are the mean of Ikonos red band, the ratio of the Ikonos blue and red bands, and the Homogeneity of the Ikonos PAN band. There are almost only spectral features but it is not surprising because the classes are defined by their color. The separability is good for the majority of the classes, but some separability of class pairs remains low. These class pairs are: water – shadow on non-vegetation, dark grey – shadow on non-vegetation, light grey – medium grey and medium grey – dark grey. For each problematic class pair, the best separabilities are calculated. The best separabilities for these problematic class pairs were obtained with spectral and textural features. Despite the color definition of the classes, the textural features play an important role to identify these classes.

5.6 Discrimination of the legend level 3

In this test, the separability is calculated between the transportation area and the building classes. The best average separabilities were found with the segmentation level 4 of the PAN Ikonos bands. The most relevant features are Angular second moment of the SPOT NIR band, the length, the length/width and the compactness. There are almost only morphological features, and it is not surprising; the transportation area and building classes are land use classes and the relationship between spectral or textural features and land use is, in most instances, both complex and indirect (Barnsley and Barr, 1997). Despite this, many land use categories have a characteristic spatial expression (Barnsley and Barr, 1997) as showed in this test.

Table 2. Distances between all classes of legend level 2 for the best average separabilities

		Group 1						Group 2				Group 3						
Classes		12	11	13	17	18	20	14	15	16	19	21	22	23	24	25	26	27
Group 1	12																	
	11	3.20																
	13	1.54	12.6						Average distance = 12.63									
	17	1.79	9.43	2.94														
	18	1.84	12.8	1.42	1.04													
	20	1.58	9.50	1.76	1.60	0.95												
Group 2	14	5.20	16.9	1.23	9.44	5.46	4.66											
	15	9.53	29.1	3.38	14.7	9.83	9.33	1.49										
	16	9.48	19.1	4.26	25.9	20.9	14.3	2.90	0.87									
	19	20.3	33.4	5.78	33.9	23.9	18.9	3.17	0.32	0.55								
Group 3	21	7.98	4.73	12.9	22.5	27.2	13.3	13.2	11.8	6.64	10.6							
	22	9.35	5.29	17.0	23.1	29.5	13.3	17.2	17.7	9.67	16.3	0.57						
	23	22.2	33.0	9.22	102	69.0	48.1	7.01	2.33	1.81	1.90	5.10	7.12					
	24	23.2	40.0	10.1	75.7	50.3	44.2	7.37	3.30	2.73	3.18	4.09	4.64	1.25				
	25	6.01	22.4	4.06	11.0	8.26	8.42	2.70	2.06	2.29	2.60	7.43	11.5	1.30	2.22			
	26	12.4	13.9	9.75	32.9	32.1	19.8	9.27	6.50	3.59	5.65	1.31	2.60	2.01	2.38	3.06		
	27	10.6	8.34	14.1	27.5	32.2	14.8	14.1	12.8	6.84	11.5	0.24	0.89	5.39	4.34	8.71	1.36	

6. CONCLUSION

All the features found in the different tests are not surprising because the features found correspond to the visual impression. But it is impossible to choose visually specific features among all the features available, and a quantitative selection, like Bhattacharyya distance, is essential to do the choice. This study shows also the utility of the morphological and textural features to classify a lot of classes, principally the non-vegetation classes, in order to overcome the poor spectral resolution, and the segmentation utility in order to calculate these features on specific region without taking into account the nearby regions. The segmentation is one of the only methods which ensure to measure the morphological features (surface, perimeter, shape…) (*Segl and Kaufmann, 2001*). These morphological features are essential in the classification of the building and transportation area classes, when many studies used ancillary data (road buffer, D.E.M., existing maps …) to classify these classes.

But, this study shows also that the multi-temporal spectral features are more effective than the spatial features, calculated thanks to the segmentation (textural and morphological features), for the discrimination of the vegetation classes and above all for the crop classes. But, the segmentation allows avoiding the "salt and pepper" effect in the classification process for these classes.

In the framework of the European CAP, a good identification of the non-vegetation classes is very important because these objects (classes) are not eligible for the subsidies. Moreover, the region-based classification of the classes like transportation area, water, tree, building … is important to have stable objects from one year to another. The segmentation of the very high resolution satellite images are also a good base for the digitalization of the crop field.

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