# FOREST OBJECT-ORIENTED CLASSIFICATION WITH CUSTOMIZED AND AUTOMATIC ATTRIBUTE SELECTION

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**KEY WORDS:** segmentation, object-oriented classification, texture, shape, radiometry

**ABSTRACT:**

This paper presents a semi-automatic method to optimize object-oriented classification without photointerpretation.
The thematic studied is the forest (Crecy forest in the north of France). A SPOT 2 image at 20 m spatial resolution was analysed in a near infrared colour composite (green, red and infrared).
New classification methods no longer work with pixels, but with regions derived from the previously segmented image [TRIAS 2006], [BENCHERIF 2009].The first step consists in image segmentation based on several criteria, a scale parameter and an homogeneity factor made up of two complementary factors: shape and radiometry.
2 segmentations have been computed: one at very large scale (no more than 20 regions) in order to establish a manually made classification with only 2 classes: forest and no forest (this latter will not be classified). Another one at a smaller scale which will be used to select the test samples (also called training area) on the forest area.
Once both segmentations and manual classification are completed and validated (essentially visually), the objective of this study is to determine semi automatically the most adapted attributes for each training area (5 training areas have been selected).
Therefore, for all selected training areas, attributes are automatically selected, consecutively based on three criteria: radiometry, shape and texture. For each of these criteria, a maximum number of attributes is fixed among all potentially interesting attributes and the optimum attribute combination is automatically selected with respect to a statistical parameter derived from a distance matrix. The distance matrix optimizes the separation between the training areas.
Then, 3 classifications were set up, each of them with the optimum automatically selected attribute combination derived from the previous step. For each of these classifications, a confusion matrix will be computed. For each training area its confusion rate with other training areas was computed and the lowest confusion rate was selected as the criterion.
For instance, if there is a training area which has 35 % of confusion pixels with other classes for a radiometric combination, 25% for a textural combination and 5 % for a morphologic one (shape criterion), this training area will be affected with a morphologic attribute combination.
The result is thus a new classification with the new customized attributes for each training area. In the assessment of this classification, the confusion rate for each class decreases significantly. Then, reliability maps are built to determine the risk of confusion between the classes.
Test results are so far encouraging. Due to this new method, the confusion rates decrease significantly with respect to a standard nearest neighbour approach.

## 1. INTRODUCTION

The classifications for optical imaging have considerably evolved in recent years. The recent introduction of object-oriented classifications based on regions instead of pixels generates much better quality classifications. The classification process has also been improved by taking into account other criteria than the reflectance of the pixels. Nowadays, the introduction of shape and texture parameters prevents this confusion.

In this paper, we propose a method of guided attribution of criteria for the different selected training areas. Therefore, three criteria will be combined: radiometry, shape and texture.

The selected study area is a forest in the north of France (Crecy forest). The tests were performed on a SPOT 2 image with 3 channels at 20 m resolution.

## 2. SEGMENTATION PROCEDURE

An object-oriented classification does not classify pixels but regions (called objects in the following sections).
This phase is very important because the quality of the future classification will directly depend on the quality of the segmentation. For this reason, some work on segmentation assessments has been done these past few years [Möller 2007], [Radoux 2007], [Weidner 2008], [Yang 1995].

### 2.1 The three criteria of segmentation

**Shape criterion**: the shape of future objects can be preferred to the radiometry of their pixels. It is an innovative concept.

Before the focus was mainly on radiometric homogeneity criteria, which was not always appropriate. For instance, if the problem is to classify buildings, it is quite possible that they have heterogeneous radiometry (lightened and shaded area on a same roof). In this case, their rectangular shape should be emphasized. Inversely if there are differently shaped objects with low radiometric contrast, they may not be differentiated with only radiometric criterion.

The shape criterion added to the radiometric criterion is equal to 1.

It means that we have to decide by looking accurately at each channel of the image to decide which is the most selective between radiometry and shape.

**Compactness criterion** (range between 0 and 1): Compactness is expressed by the following mathematical formula:

$$\frac{l_v w_v}{\# P_v} \quad (1)$$

Where

$l_v$ = object length,
$w_v$, = object width
Pv = total number of pixels in the region.

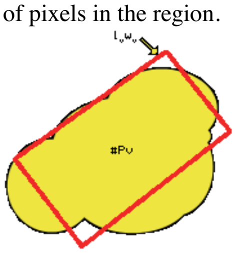

Figure 1. Compactness criterion

If compactness is low, the objects will be rather elongated and if high condensed.

**Scale factor criterion:** the scale factor will have a direct impact on the size of the objects and therefore, their number inside the image. If it is high, there will be few objects (sub-segmentation). If it is low, there will be many objects (over-segmentation). The scale parameter represents a standard deviation of the shape and radiometric criterion. Thus it depends on the size of regions.

### 2.2 Application to our study

In the case of our study, two segmentations will be performed (Figure 2 (b) and (d)):

One at a very large scale (about 20 objects) in order to perform a very basic manual classification into two classes: forest and non forest. (Figure 2 (b)).

Another one at a smaller scale (2,224 objects in the forest) will be used to select training areas only issued from forest area (Figure 2(d)).

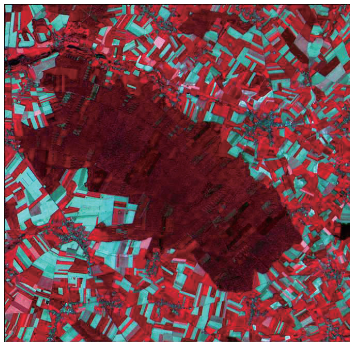

Figure 2 (a). Extract from a SPOT image of the Crecy forest at 15m resolution.

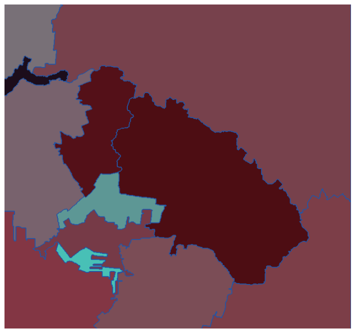

Figure 2 (b). Segmented area with 0.5 shape factor, **150 scale parameter,** 0.5 compactness.

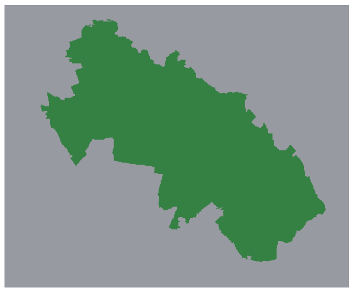

Figure 2 (c). Objects merged and classified into forest and non-forest.

Figure 2 (d). Segmented area with 0.5 shape factor, **25 scale parameter,** 0.5 compactness.

### 2.3 Choice of training areas

Training areas will now be selected among all the objects derived from the small scaled segmentation.

The forest is slightly homogeneous (from a radiometric point of view) which makes classification difficult. However, near infra red (NIR) was chosen as the most selective criterion to determine our training areas because the range values in NIR are the highest of the three channels.

Five classes in NIR were therefore chosen (cf. figure 3):

- Class 1: 2 samples, 65.5average,
- Class 2: 2 samples, 77 average,
- Class 3: 2 samples, 83 average,
- Class 4: 2 samples, 86.5 average,
- Class 5: 3 samples, 95 average.

These classes belong to the “mother (master)” class forest, so they do not leave the forest perimeter (Figure 4).

Figure 3. Selected training areas

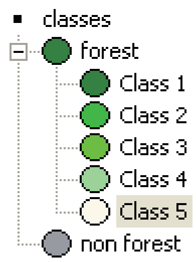


Figure 4. Class Hierarchy

It can be observed that the average of NIR values does not differ significantly, which justifies the use of other criteria to improve class selection in future.

## 3. AUTOMATIC SELECTION OF RADIOMETRIC, SHAPE AND TEXTURAL ATTRIBUTES USING A DISTANCE MATRIX.

The technique used consists in choosing a fixed attribute number for each class according to the three criteria: radiometry, shape and texture and in selecting the best performing combination.

The term "performing" means that a distance matrix must be calculate for each combination. The minimum distance of each matrix is extracted and the maximum of these distances defines the best performing combination. Indeed, the more distant the gravity centres of the training areas are from each other, the more the quality of the classification will be improved, thus generating less confusion between classes.

Let us consider what happens with each criterion.

### 3.1 Radiometry

We selected all the criteria relating to the average radiometric standard deviation values of the three channels (Green, Red and Near Infrared), i.e. six criteria in all.

Three criteria were optimized; that is to say, that a distance matrix was calculated for each possible combination of three criteria among the six selected.

A higher number of criteria is not necessary, as shown in Figure 5. Indeed, it is clear that the separation distance decreases when there are more than three dimensions.

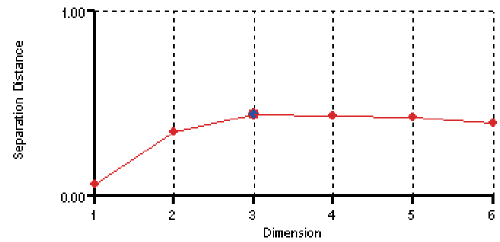


Figure 5. Separation distance in terms of dimension of attribute space

The following combination was selected as providing the maximum distance of 0.44 (0.44 being the minimum distance of distance matrix in Figure 6):

- Standard deviation on channel 3,
- Mean layer on channel 2,
- Mean layer on channel 3.

| Class/Class | Classe 1 | Classe 2 | Classe 3 | Classe 4 | Classe 5 |
|---|---|---|---|---|---|
| Dimension: 3 | | | | | |
| Classe 1 | 0.000000 | 1.511153 | 4.929238 | 5.648478 | 11.176630 |
| Classe 2 | 1.511153 | 0.000000 | 1.227779 | 1.131780 | 5.367957 |
| Classe 3 | 4.929238 | 1.227779 | 0.000000 | 0.441234 | 2.662450 |
| Classe 4 | 5.648478 | 1.131780 | 0.441234 | 0.000000 | 2.078747 |
| Classe 5 | 11.176630 | 5.367957 | 2.662450 | 2.078747 | 0.000000 |

Figure 6. Distance matrix for radiometry criterion (0.44 is the smallest distance).

The same procedure can be applied for shape and texture.

### 3.2 Shape.

Among all existing shape parameters, as well as radiometry, the combination providing maximum distance consists in three criteria.

These three criteria are:

**Main direction:** the main direction of an image object is the direction of the eigenvector belonging to the larger of the two eigenvalues derived from the covariance matrix of the spatial distribution of the image object. This attribute is used to determine whether the objects have a main direction or not.

**Elliptic Fit:** this attribute is used to determine if the regions are closer in shape to an ellipse or not.

**Asymmetry:** this attribute measures the asymmetry of the regions.

| Class/Class | Classe 1 | Classe 2 | Classe 3 | Classe 4 | Classe 5 |
|---|---|---|---|---|---|
| Dimension: 3 | | | | | |
| Classe 1 | 0.000000 | 3.140978 | 3.149894 | 2.713938 | 1.680152 |
| Classe 2 | 3.140978 | 0.000000 | 0.835475 | 1.169827 | 0.785194 |
| Classe 3 | 3.149894 | 0.835475 | 0.000000 | 1.142442 | 0.894999 |
| Classe 4 | 2.713938 | 1.169827 | 1.142442 | 0.000000 | 1.308051 |
| Classe 5 | 1.680152 | 0.785194 | 0.894999 | 1.308051 | 0.000000 |

Figure 7. Distance matrix for shape criterion (0.78 is the smallest distance).

### 3.3 Haralick Texture based on the Gray Level Co-occurrence Matrix (GLCM)

Among all the textural parameters, the three criteria selected are:

**GLCM Correlation Layer 2:** Measures the linear dependency of grey levels between neighbouring pixels [cf. Definiens reference book].

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^{2})(\sigma_j^{2})}}\right] \quad (2)$$

Where

i: the row number
j: the column number
Pi,j: the normalized value in the cell i,j
N: the number of rows or columns
µi,j: GLCM mean
σi,j: GLCM standard deviation

**GLCM Homogeneity Layer 2 and Layer 3**: If the image is locally homogeneous, the value is high if GLCM concentrates along the diagonal. Homogeneity weights the values by the inverse of the contrast weight with weights, decreasing exponentially according to their distance to the diagonal [Definiens reference book].

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (3)$$

Where

i: the row number
j: the column number
Pi,j: the normalized value in the cell i,j
N: the number of rows or columns

All these parameters are computed in all directions.

| Class/Class | Classe 1 | Classe 2 | Classe 3 | Classe 4 | Classe 5 |
|---|---|---|---|---|---|
| Dimension: 3 | | | | | |
| Classe 1 | 0.000000 | 2.017614 | 1.209389 | 1.289811 | 3.014988 |
| Classe 2 | 2.017614 | 0.000000 | 2.028403 | 1.650397 | 4.705186 |
| Classe 3 | 1.209389 | 2.028403 | 0.000000 | 1.230844 | 3.993212 |
| Classe 4 | 1.289811 | 1.650397 | 1.230844 | 0.000000 | 5.370173 |
| Classe 5 | 3.014988 | 4.705186 | 3.993212 | 5.370173 | 0.000000 |

Figure 8. Distance matrix for texture criterion (1.23 is the smallest distance).

## 4. CLASSIFICATION USING STANDARD NEAREST NEIGHBOUR APPROACH

### 4.1 Principle

The objects are classified following a nearest neighbour membership value concept.
The membership value is the probability for an image object of belonging to a training area (future class) among the selected samples.

All classification algorithms based on probabilistic criteria using the mathematical concept of fuzzy logic [Bloch 2003]. In contradiction with Boolean logic (belonging or not belonging), it can deal with criteria for membership between 0 and 1 (membership of 60% for example).

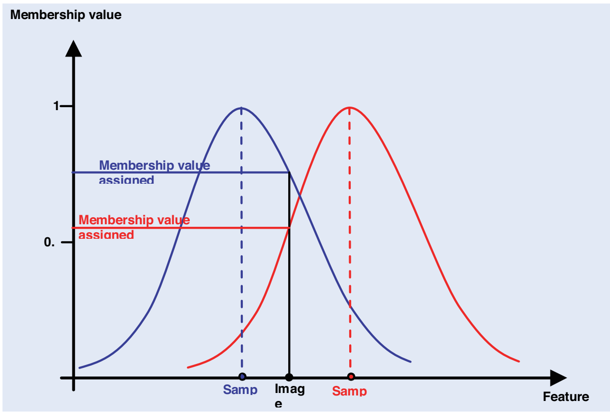


Figure 9. Membership of a class according to the principle of fuzzy logic.

In the previous example, it was clear that ”Image object” belonged to the red class, because its membership value for this class was higher than for the blue one.

### 4.2 Classification results

At this level, three standard nearest neighbour classifications will be performed using these selected attributes (see Figure 10 (a), (b) and (c)).

Standard Nearest Neighbours means that the previously selected attributes will be assigned to all training areas.

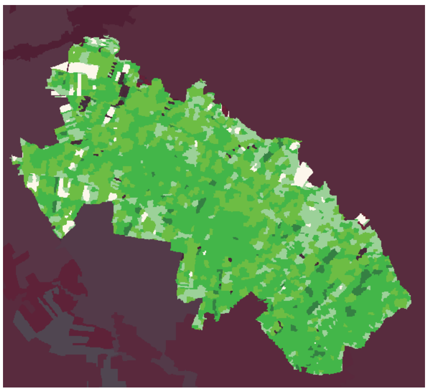

Figure 10 (a). Classification derived from Standard Nearest Neighbour radiometric attribute

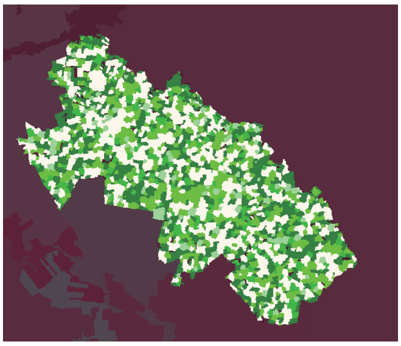

Figure 10 (b). Classification derived from Standard Nearest Neighbour shape attribute

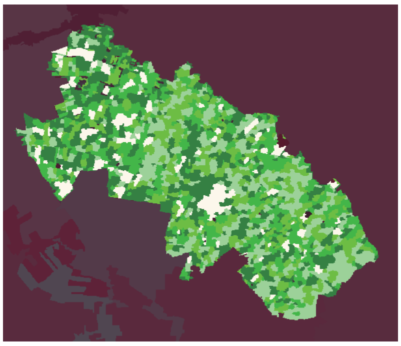

Figure 10 (c). Classification derived from Standard Nearest Neighbour textural attribute

## 5. CLASSIFICATION USING NEAREST NEIGHBOUR

Once the regions are classified, the results will be analyzed to build a "mixed" classification in which the attributes of each training area will be individually selected in terms of a quality indicator.

This quality indicator can be characterised in two different ways:

- By compiling statistics on membership values for each class,
- By computing a confusion percentage for each training class derived from a confusion matrix.

The first criterion does not seem discriminating enough. In fact, it is too dependant on the neighbours' slope function.

The second is preferable, being more significant.

For each training area the attributes group (radiometry, shape or texture) generating the lowest confusion rate will be selected in relation to the other training areas.

<u>**Choice (minimum confusion rate for each class)**</u>
**Class 1:** shape 51%
**Class 2:** radio 38%
**Class 3:** radio 32%
**Class 4:** texture 11%
**Class 5:** radio 0%

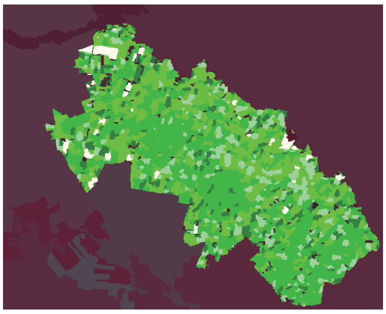

Figure 11 (a). Mixed Classification

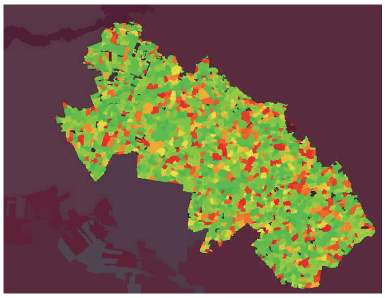

Figure 11 (b). Stability Map (green: small confusion probability, red: high confusion probability)

**Region of Interest as Ground Truth (Percent)**
Kappa: 83.62

| **Class** | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 |
|---|---|---|---|---|---|
| unclassified | 0 | 0 | 2,94 | 0 | 0 |
| Class 1 | 75 | 0 | 10,5 | 4,35 | 0 |
| Class 2 | 11,33 | 81,93 | 0 | 5,14 | 0 |
| Class 3 | 13,27 | 0 | 85,71 | 3,95 | 0 |
| Class 4 | 0 | 18,07 | 0 | 78,66 | 0 |
| Class 5 | 0 | 0 | 0,84 | 7,91 | 100 |

Figure 12. Confusion matrix derived from mixed classification.

This shows the contribution of a classification using optimized attributes for each training area compared to uniform selection of attributes.

## 6. CONCLUSION, PERSPECTIVES.

A semi-automatic method to optimise an object-oriented classification with statistical parameters without photointerpretation was adopted.

Object-oriented classifications are very powerful because they can adapt attributes of the training areas to their characteristics to improve classification quality.

Pixel-based classifications should not disappear but are less efficient because they depend solely on radiometry.

This method could be strengthened by ground truth assessment. Furthermore, it would be interesting to adapt this approach to more varied urban or rural landscapes.

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