HEDGEROW DETECTION IN HRS AND VHRS IMAGES FROM DIFFERENT SOURCE (OPTICAL, RADAR)

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ABSTRACT

The challenge of recreating a green belt (hedgerow, forest, green corridors ...) is to restore biodiversity that the ecological continuity required. A coherent ecological network allows species to move, interact, and continue to support human being.

The main objective of this paper is to explore the potential of image processing methods to map hedgerows, corridors, woodlands of the green belt. We present a methodology based on unsupervised and supervised classification, segmentation and classification fusion. It is applied to a rural landscape and several sensors: Very High and High Resolution, optical and radar satellite, respectively FORMOSAT-2 (8m) SPOT 5 (2.5m and 10m) and TerraSar-X (3m).

Index Terms— hedgerow detection, classification, supervised/unsupervised techniques.

1. INTRODUCTION

The "green belt" is a concept which was developed in the 1980's-1990's by the French Government (the Grenelle Environment Forum) [1]. This concept covers different realities: urban planning, landscape, environment, urban ecology, etc... Creating a green belt is a gain to ecosystem and biodiversity. It usually has a threefold purpose to restore, protect and manage biodiversity in situ. Although small landscape elements such as hedgerow, thickets, groves, scattered trees and grass strips are only a small part of agricultural land, their role in maintaining biodiversity is largely recognized [2]. Beyond their ecological functions (shelter and habitat for some species, corridor effects, etc), these landscape elements play an important role in soil conservation (protection against erosion) and limiting pollution from Agricultural (biogeochemical barrier).

The main objectives are to explore the potential of image processing methods to map the hedgerows, corridors, woodlands constituting the green belt and to find the most automatic and efficient methods. One objective is also to test the discriminating power of the various satellite resolutions. Technics and methods will be different for several type of sensors.

The methodology is tested on Very High Spatial Resolution (VHRS) sensors: radar with TerraSar-X (3m), optical satellite with SPOT 5 (2.5m) and FORMOSAT (8m). The principle adopted is primarily unsupervised classification that makes the process more automatic. We test supervised mode thanks to ground-truth when they are available. Result validation is the most complex part; Hedgerow is a particular thin heterogeneous multiform and linear "object", The sampling is delicate and difficult, but it is necessary to validate the proposed methodology.

We will focus on the extraction of the small wooded elements and provide a detailed map of Hedgerow and wooded areas in the southwest of Toulouse (France).

2. METHOD

Different author presented supervised method to detect and characterize Hedgerow [3], [4], [5], [6] and [7].

For large areas and large scales monitoring, we develop a methodology which combines unsupervised and supervised processes (figure 1). The goal is to take advantages of these both techniques to improve Hedgerow detection. For example, linear objects are better distinguished in unsupervised classification. The different steps are:

- Automatic segmentation consists of dividing the image into homogeneous connected areas with closed contours (watershed basin) [8].
- Creating and classifying textural images to detect heterogeneity and linearity.
- ICM (Iterative Conditional Mode) classification: fuzzy contextual algorithm based on a Markovian model for supervised and unsupervised classification using temporal segmentation [9].
- Unsupervised classification based on iterative principle that increases the influence of context and segmentation parameters. The algorithm refines the classification by giving more weight to contextual information through a temperature parameter T (as for the simulated annealing algorithm).

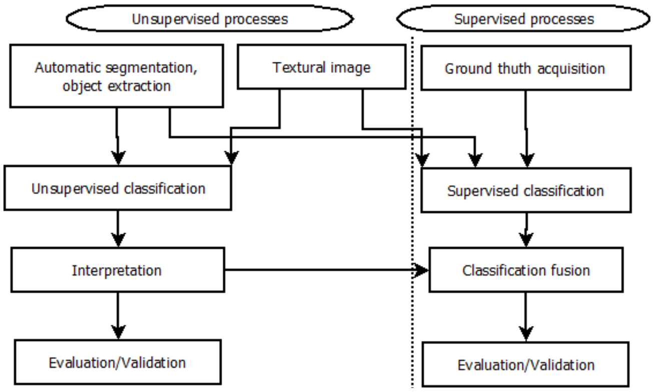

Figure 1 : Flowchart of the presented methodology

- Constitute a Hedgerow "database" for the interest areas of supervised classification and verification of results for unsupervised and supervised mode.
- Fusion of classification images (supervised with unsupervised or supervised [10]). Automatic fusion in the supervised mode is the combined use of several classifications that minimizes automatically confusion between classes and maximizes quality indices (without the intervention of an expert).
- Result evaluations: classification quality is compute from a confusion matrix (in supervised mode) and a spatial correspondence (unsupervised mode).

3. APPLICATIONS

The OSR (Regional Spatial Observatory) study area is located the Southwest of Toulouse (France)**.** The OSR collects and organizes in-situ and remotely-sensed data in order to serve pluridisciplinary research works on various environmental issues. It favors the development of tools and services for territories management through space technologies applications, falling within the framework of the "Global Monitoring for Environment and Security (**GMES**) downstream services**"**. The available images are listed in Table 1.

3.1. Experimental evaluation

Learning and checking samples are selected to validate the results. They are digitized from BD ortho® database (the IGN's (national geographic institute) administrative department-based orthophotography, digital reference tool) or Google earth© (figure 2), and photo-interpretation of satellite images. This allowed us to define kind of hedges (low and high hedges).

Application to Formosat-2 images (8m)

With supervised classification the rate of success for Hedgerow class (90% correctly detected) is high, but Hedgerows are very extended and over represented. With unsupervised classification (figure 3): we identify 9 green belt classes; some of them are mixed with woodland, brush or scrub. Hedgerows are clearly visible, well designed and separated with roads. They are sometimes not complete: where vegetation density approaches forest density, parts of dense hedges tend to be classified in Hardwood class. Hardwood and conifer are well classified (99%). These results are closer to reality than supervised mode, despite a light deficit (omission) of Hedgerow detection. Thus, we keep this unsupervised classification (figure 2).
With the pixel size of FORMOSAT (8m * 8m), the mixel effect becomes important. A pixel belonging to a small area (such as narrow hedges) is influenced by its neighbors and thus it is assigned to another class. This effect can be crucial for the accuracy when an area includes more crop than hedge, in this case some hedgerows disappear. The opposite phenomenon happens: dilation effect that implies overrepresentation of hedge.

Application to 2010 Spot-5 images (2.5 m, panchromatic fusion)

In supervised classification the rate of success for hedgerow is high (95% correctly detected), hedgerows are very extended too and over represented but less than with Formosat-2 application. Fusion of interpreted unsupervised and supervised classifications gives 6 kinds of hardwood (from unsupervised classification) and removes hedgerow confusions with hardwood classes (figure 4).

Application to2008 TerraSar-X images (3 m)

The method is unsupervised classification with adding textural images obtained from variation coefficient calculated on neighborhood. The radar backscattering over hedges is generally produced by strong double scattering (ground-to-hedge), due to their vertical structure, a phenomenon found with walls of buildings versus ground. It allows recognizing hedgerows, but they are confused with built areas. To differentiate built areas from hedgerows, we compute heterogeneity index from the previous classification. An image is derived from this heterogeneity index. Built areas are very heterogeneous, more than Hedgerow and thus can be differentiated. This image is fused with the first unsupervised classification (figure 5).

We only use unsupervised classification because of the difficulty to take Hedgerow samples. Hedgerows are clearly visible. They consist in two parallel linear structures: a dark part and the other brilliant. The bright one represents the hedgerows and the dark one the shadow of the hedge. But it is not always so distinct. The brightness is a result of a well known physical phenomenon: the effect of the aspect angle on the double bounce of trunks.. The wave hits at the first time the ground which is a surface highly reflective and after the tree trunk.

Table 1: Available images of the study area.

Satellite	Sensor type	Resolution	Useful area	Year	Number of images	Dates
Formosat-2	Optical	8 m	59,788 ha	2007	8	23/02, 4/04, 30/05, 30/06, 7/07, 4/08, 15/09, 13/10
Spot 5	Optical	10/2.5 m	18,750 ha	2010/2011	3	27/06/2010, 20/09/2010, 16/01/2011
Terrasar X	Radar	3 m	9,650 ha	2008	5	28/09, 09/10, 20/10, 31/10, 11/11

Figure 2: Google map image of an extracted area (5kmby3km, 1,500ha).

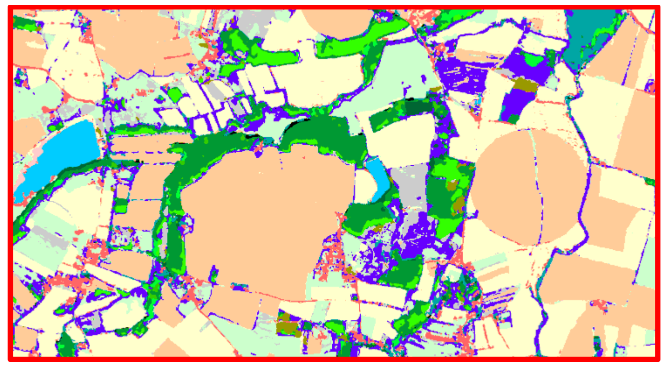

Figure 4: SPOT5 fusion of unsupervised and supervised classification (green: woods and riparian, purple: hedgerows, pink: built area/ mineral surface, light green: grassland, yellow and orange: winter and summer crop, blue: water).

Figure 3: Formosat-2 unsupervised classification (green: woods and riparian, purple: hedgerows, pink: built area/ mineral surface, light green: grassland, yellow and orange: winter and summer crop, blue: water)

Figure 5: TerraSar X unsupervised classification (green woods and riparian, purple: hedgerows, pink: built area/ mineral surface, blue: water)

Thus, the specular scatter received by the sensor is very important, which implies strong reflectance near hedges.
The results with only unsupervised classification is 75% correctly classified

3.2 Result comparisons

Results between Formosat-2 (8m) and Spot 5 (2.5m) are quite similar, but we can note that with an 8m resolution, supervised classification is less accurate for Hedgerow extraction due to checking samples which contain mixels (some hedgerows width are sometimes less than 8 meters).
However, with a 2.5m resolution, samples are more significant, so supervised classification gives good result. However we can exploit the complementarity of supervised and unsupervised classification to improve Hedgerow detection.
For Terrasar-X application, we only use unsupervised classification, Hedgerows are recognized but they present more deficit than Formosat2 and Spot5applications.

For these 3 applications, unsupervised method gives similar results: Hedgerow detection is accurate but some small wooded elements are missed, which are improved by the supervised method.

4. CONCLUSION

The presented method is validated on three sensor types. For unsupervised classification, we find several hedgerow classes: some of them are correctly represented and others are confused with woodland classes. We observe hedgerow deficit (omission error) or surplus (commission error). Hedgerow detection is sensitive to the residual error of multi date image rectification. This residual error for multi date images and also mixel problems imply an over representation of hedgerow class mainly in supervised classification process.

We can conclude that hedgerows are detected for a resolution between 2.5 and 8 meters. Multitemporal data is important, a minimum of 3 dates is necessary for an accurate detection. Fusion between supervised and unsupervised classification gives a balance between excess and deficit of class Hedgerow (commission and omission errors are reduced).

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