EXTRACTION OF LANDCOVER THEMES OUT OF AERIAL ORTHOIMAGES IN MOUNTAINOUS AREAS USING EXTERNAL INFORMATION

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ABSTRACT:

In mountainous areas, the landcover extraction out of orthoimages through semi-automatic classification is limited by several factors (such as large shadow areas, radiometric similarities between different themes, inhomogeneous radiometry among regions of the same class...). Image information is not sufficient to separate the different classes. Nevertheless, good results can be obtained by dividing each landcover class "*c*" into two subclasses "*c in shadow*" / "*c not in shadow*" and introducing external information in the classification process. This information can be an older or more generalized database, geographic knowledge concerning the links between relief and landcover, or prior information concerning shadows. This external knowledge is then interpreted in terms of *a priori* probabilities and merged with radiometric information from the image in a *MAP* per region classification process. Besides, the results can also be improved by the use of combinations of channels calculated from the initial image.

1 INTRODUCTION

The French National Mapping Agency (IGN) is designing a new 1/25 000 national base map. This new map must be produced from the IGN's national digital databases through a fully digital process, which must be as automatic as possible. Nevertheless, some legend items are not present in the IGN's digital databases whereas they are necessary to obtain a correct map. In the special case of mountainous areas, important landcover information lacks from the IGN's digital databases. More precisely, information about the themes rocks, screes and glaciers is not available whereas their representation is necessary in mountainous area maps. As a consequence, this missing information must be gotten from other sources. It can be extracted either from present maps or from aerial images. As the cartography of these missing landcover themes is not up to date in present maps, the second solution has been chosen (Le Men et al., 2002). Furthermore, it offers the possibilty to be used afterwards for map updating.

To sum up, the chosen solution consists in extracting landcover information out of aerial orthophotos through a supervised classification method in two steps : the images are firstly segmented (by the tool presented in (Guigues et al., 2006)) in homogeneous regions which are then classified knowing statistical radiometric models of the classes previously computed from training data (as described in (Trias-Sanz and Boldo, 2005)). The orthoimages come from the IGN's orthoimages database, which contains digital colour orthophotos with 3 or 4 (red - green - blue - near infrared) bands and with a 50cm resolution. To obtain a landcover classification of the whole area, the six following classes are defined : lakes - forest - pasture - rocks - screes - glaciers.

This landcover supervised classification problem could seem quite easy since few themes are seeked. However, it is perturbed by several phenomena such as important radiometric variations or shadow areas, so that image information is not sufficient to separate the different classes. A previous study (Le Men et al., 2002) has shown it was possible to improve the results by correcting the radiometry in shadow zones and by introducing external knowledge in the classification process. Nevertheless, this correction of radiometry was limited by uncertainties on the DTM and on images'capture time. Therefore, a simpler variant of this method without radiometric corrections has been tested in a new study. It is presented in this paper. The results obtained with this new method are equivalent to these obtained with the old one and are suitable for the base map's purposes.

In this paper, the different radiometric phenomena perturbing the classification will firstly be presented. Secondly, solutions consisting notably in taking knowledge from external sources into account, in taking shadows into account by the means of classes divided into two "shadow/non shadow" subclasses and in using combinations of derived channels computed from the orthoimages'bands will be proposed. The classification method and the way external information is taken into account will then be developped. In last section, experimental results will be presented.

2 PROBLEMS

In mountainous areas, an automatic land-cover extraction is perturbed by several phenomena causing misclassifications : image information is not sufficient to separate some classes.

2.1 Shadow areas

There are very large shadow areas in the images because of the strong variations of the relief as on figure 1. The landcover themes concerned by shadows are mostly rocks, screes and glaciers. As the radiometry of pixels belonging to a same landcover class is obviously completely different whether they lie in shadow or not, it is necessary to take the shadow areas into account in order to obtain a correct classification of the whole zone.

2.2 Radiometric variations inside a class

The radiometry of pixels belonging to a same class greatly varies from a part of the image to another. These variations can be :

Figure 1: Example of large shadow area : the radiometry of pixels of a same class is different whether they lie in shadow or not

- "natural" - It means related to changes, for instance in vegetation or geology inside the image area.
- related to illumination variations - In mountainous areas, these variations are very important because of the rough relief : the sky illumination and the ground illumination can greatly vary from a point to an other as on figure 2. The problems of shadows mentioned above are an extreme situation of illumination effects.

Figure 2: Example of illumination variations due to the relief

- "artificial" - The classified orthoimages are in fact a mosaic of orthorectified aerial photographs which have not been captured at the same time (or even the same day). Moreover, they have undergone several radiometric treatments (such as image dodging...) which have sometimes increased variations of radiometry inside a same class from a part of the orthoimage to an other.

2.3 Classes with similar radiometry

Distinct classes can have similar radiometric distributions, as for example some screes (especially riverbed screes) which are almost as light as glaciers or lakes which are often difficult to distinguish from rocks in shadow, or even rocks and screes. Besides, this phenomenom is increased by the variations of radiometry inside a same class previously described.

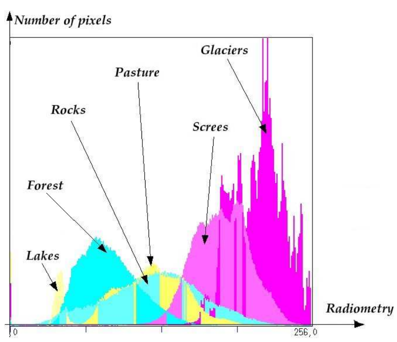

Figure 3: Image histogram for "value" channel.

3 PROPOSED SOLUTIONS

3.1 Shadow/non shadow classes

As it was said in the previous section, it is necessary to take into account the shadow areas to obtain a correct classification of the whole image.
A first way to achieve this could consist in correcting the radiometry in shadow areas (after having detected them). However, in the present case, this correction would be limited by several uncertainties : the orthoimage to treat is a mosaic of merged aerial orthophotographs which have undergone several (sometimes hand-made) unknown radiometric treatments and of which the precise time of capture is no more available. Moreover, the accuracy of the available digital terrain model is about 10-20m in mountainous areas. Nevertheless, a method to deal with these uncertainties to correct the radiometry in shadows areas was proposed and used in a previous study (Le Men et al., 2002).
As the main problem with shadows is the fact that the radiometric model of a class will be completely different in shadow and in light, the chosen solution consists in dividing each class "*C*" in two classes "*C in shadow*" and "*C in light*" so that two distinct models are obtained for each landcover theme. At the end of the classification process, the two subclasses "*C in shadow*" and "*C in light*" are merged.
However, the approximate time of image capture and the DTM can be used to give each pixel a probability of being in shadow (see 3.2.3).

3.2 Introduction of external knowledge in the classification process

Because of the important radiometric variations inside a class and the radiometric similarities between distinct classes, the image information is not sufficient to obtain a correct classification. A previous study has shown that the introduction of external knowledge in the classification process could improve the results. Furthermore, it can help to obtain a more generalized result, which is usefull in the present mapping context where only zones with a cartographic meaning are required. This information is interpreted as *a priori* probabilities in a MAP classification method (described in 4.2) (Trias-Sanz, 2006) (Le Men et al., 2002).

3.2.1 Information related to the relief In mountainous areas, the landcover is strongly related to the relief, it means to altitude, slope and orientation. Those variables are easily computed from the DTM. As a consequence, knowing geographic information such as the lowest and highest limits of the landcover themes or the influence of orientation on landcover (especially glaciers and forest), it becomes possible to define for each landcover theme a probability model function of those variables. Such a model is proposed in (Le Men et al., 2002) from (Elhai, 1968) and (Lacambre, 2001). It consists of two distinct models P_{alti} and P_{slope} (respectively one for altitude and another for slope information) made of the following simple piecewise linear functions drawn in figure 4.
As the orientation has an important influence only on forest and glaciers, this is taken into account only for these themes. Probability model knowing altitude, probability model knowing slope and influence of orientation are merged by the following formulas :

$$P_{model}(forest|altitude{=}h, azimuth{=}az, slope{=}s) = P_{alti}(forest|altitude{=}h{+}s\cdot cos(az)) \cdot P_{slope}(forest|slope{=}s)$$

$$P_{model}(glacier|altitude{=}h, azimuth{=}az, slope{=}s) = P_{alti}(forest|altitude{=}h{-}s\cdot cos(az)) \cdot P_{slope}(glacier|slope{=}s)$$

$$P_{model}(t|altitude{=}h, azimuth{=}az, slope{=}s) = P_{alti}(t|altitude{=}z) \cdot P_{slope}(t|slope{=}s) \quad \text{for another theme } t$$

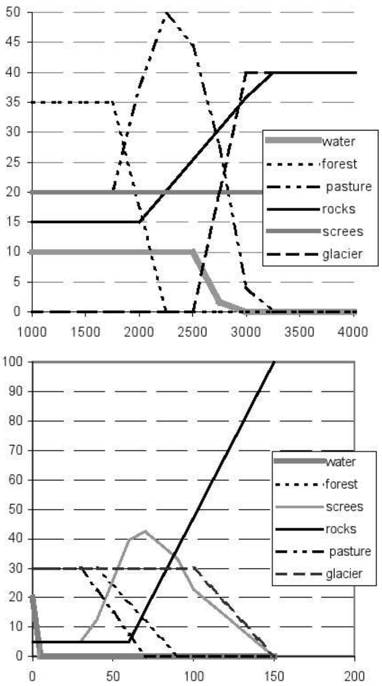

Figure 4: Prior probability (in %) to find the different landcover themes knowing altitude (in meters) and slope (in %)

The final probability *P(theme=to|altitude,orientation,slope)* is equal to $\frac{P_{model}(theme=to|altitude,orientation,slope)}{\sum_{t\in legend} P_{model}(theme=t|altitude,orientation,slope)}$
For example, the probability to find rocks knowing the DTM is shown on figure 5.

3.2.2 Other databases Knowledge from other available data bases can also be used.
In the present case, prior information from CORINE Land Cover 2000 (CLC2000) database was introduced in the classification process. This digital landcover European geographic database has been made from satellite images (captured in the year 2000) by means of photointerpretation (CORINE Land Cover, last visited on the 31st of January 2007) (Bossard et al., 2000).

Its scale (1/100 000) is smaller than the one of the national base map (figure 6). As a consequence, this information must be considered as imprecise since the CLC2000 regions are too generalized and may contain distinct themes of the base map classification.
Furthermore, the semantic precision is different from the one of our six items legend. CLC2000 is sometimes more precise - for instance, in CLC2000, different kinds of forest are discriminated - or on the contrary less precise - for example, CLC2000's "rocks" class includes rocks and screes. It also offers "intermediate" themes such as a sparse vegetation class which concerns screes, pasture, rocks... Therefore the introduction of prior information from CLC2000 in the classification process must deal with those uncertainties. That's why CLC2000 is interpreted in terms of probability with an empirical probability model : for each CLC2000 item $T_{CLC2000}$ and each classification class $T_{classif}$, a probability value $P(T_{classif}|T_{CLC2000})$ is empirically fixed. Several such models have been tested.
The geometric uncertainties have not been taken into account since no general rule (such as "a CLC2000 class A region always goes over a CLC2000 class B region") has been noticed.
An older database could also be used (in an updating context for instance). In this particular case, the uncertainty comes from evolution and also mostly lies in the geometry of the regions. As a consequence, it could be modeled by a probability function such as a regression or a progression function.

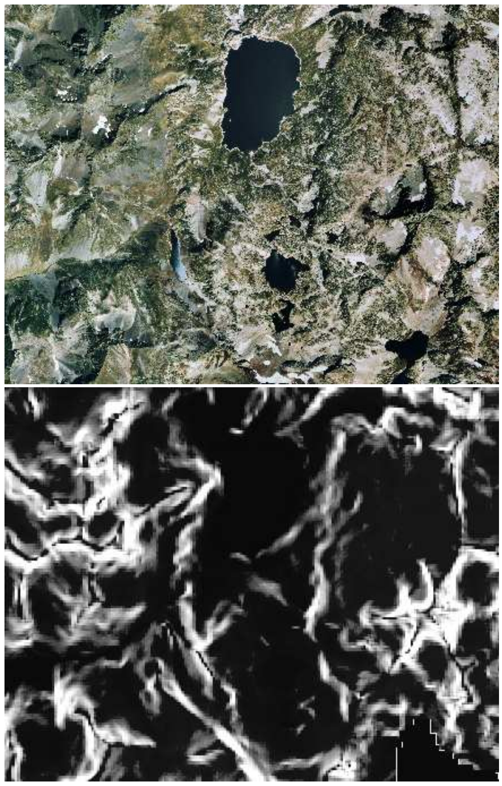

Figure 5: Prior probability to find rocks knowing the DTM

Figure 6: CLC2000 is a smaller scale database with a different nomenclature

3.2.3 Shadow/non shadow prior information Even though the available information is not sufficient to precisely detect shadows, it is possible to use it to compute a prior probability for each pixel of the image to lie in shadow knowing the DTM (figure 7). The exact capture times of the different aerial photographs merged in the orthoimage are not precisely known, but the beginning and final time of data capture of all these images are known. So a probability for each image pixel to be in shadow can be computed with the following method :
- Every five minutes between the beginning and the end of the images'acquisition, the Sun's position is computed and then the

shadows are estimated knowing the Digital Terrain Model : a pixel (it means a point of the DTM) is in shadow if it is hidden from the Sun by another point of the DTM.
- In the end, the probability that a pixel is in shadow during the data acquisition interval is computed as the number of five minutes periods (of this interval) during which it lies in shadow divided by the total number of five minutes periods of this interval. No special care is taken concerning the DTM precision.

Figure 7: Shadow prior probability knowing DTM

3.3 Derived channels

New channels can be computed from the original bands of the orthoimage (Trias-Sanz, 2006). They can be texture channels, indexes or simple functions of the original channels. The classification result can be improved using a combination of these derived channels. For instance, $NDVI$ (Normalized Difference Vegetation Index) channel is very usefull to discriminate vegetation. That's why several combinations of derived channels have been tested.

4 METHOD

The orthoimage is first segmented into homogeneous regions. These regions are then classified through a *MAP* classification algorithm taking into account external knowledge as prior probabilities.

4.1 Segmentation

First of all, the image must be segmented into homogeneous landcover regions. This is achieved thanks to the multi-scale segmentation method described in (Guigues et al., 2006) and (Guigues, 2004). This tool allows to compute a pyramid of segmentations of the image. Each level of this pyramid corresponds to an alternative between detail and generalization. This pyramid is then cut at a level empirically chosen to obtain a suitable image partition. The choice of this level is a compromise between detail and the size of regions since on one hand, in an over segmentation, some regions will be too small to have meaning and will be at risk to be misclassified whereas on the other hand, in a too coarse segmentation, wide regions will contain different landcover items. In the present case, the goal is to obtain a quite generalized result and the main difficulty was to find a level allowing to discriminate distinct themes (such as glaciers and rocks) in shadow without any over-segmentation of lit zones. More particularly, lit forest areas tend to be easily over segmented since they contain many small shadows due to differences of height between trees. Nevertheless, the use of downsampled images decreases this over-segmentation problem. Moreover, this reduces the computing time.

4.2 Classification

The segmentation's regions are then classified by the classification tool presented in (Trias-Sanz, 2006) and (Trias-Sanz and Boldo, 2005). This tool works in two steps :

1. Model estimation from training data captured by an operator First, for each class, the best parameters of several statistical distributions (such as gaussian, laplacian laws but also histograms (raw or obtained by kernel density estimation)...) are computed to fit to the radiometric n-dimensional histogram of the class (with n number of channels used for the classification). Then the best model is selected thanks to a Bayes Information Criterion which allows to choose an alternative between fit to data and model complexity.

2. Classification : The image can then be classified knowing the probability model of the radiometry of the different classes. Several per pixel and per region classification methods are proposed in (Trias-Sanz, 2006).

In the present case, a *MAP* per region classification algorithm is used. Such a method allows to take easily into account external information (from relief, from CLC2000 and concerning the shadow probability in the present case) as prior probability. With this classification method, the label $c_o(R)$ given to a region R is its most probable class according to the radiometric model previously estimated and to prior probabilities. Hence, $c_o(R)$ is the class c that maximizes the following function :

$$\prod_{i\ extern\ information\ source} (P_i(c(R)=c))^{a_i} \cdot \left(\prod_{pixel\ s\in R} P_{radiometricmodel}(I(s)|c(s)=c)\right)^{\frac{1}{Card\ R}}$$

with $I(s)$ standing for the radiometry vector of pixel s, $c(z)$ meaning region or pixel "z's class" and $P(c(z)=c)$ standing for the probability for pixel or region z to belong to class c. the a_i terms stands for weight parameters balancing the different prior probability sources.

5 TESTS AND RESULTS

Tests were carried out on two zones : the first one is located near Saint-Christophe-en-Oisans (in the Alps) where only an old 3-bands argentic scanned orthoimage with many radiometric problems was available. All the landcover themes of the classification are present there. This was already the test zone of the previous study (Le Men et al., 2002), so it was interesting to compare the new results to the ones previously obtained.
The second test zone has been chosen in the Pyrenees, in the neighborhood of the Pic du Midi d'Ossau since 4-bands orthoimages (captured by a digital camera) are available there. No real glacier (just small remaining snow regions) is present in this zone, but all the other classification items are present there.

5.1 Tests on several parameters

5.1.1 Channels combination Many channels combinations have been tested. Those tests have shown that several channels combinations give quite good and almost equivalent results. Value, hue and NDVI (when infrared band is available) channels is one of the channels combinations giving the best results. The three Karhunen-Loève color space channels give good results too (Wang et al., 2003). Value, hue and a log-opponent chromaticity channel (Berens and Finlayson, 2000) has also allowed to obtain good results on the Alps'test zone.
Those tests have also shown that the use of texture channels does not improve the classification and tends to bring too generalized results and misclassifications between distinct themes having similar texture.

5.1.2 Prior information about shadows The tests have shown that this information is useful to prevent misclassifications such as the ones between lakes and rocks in shadow (as on figure 8). It also helps to discriminate glaciers in shadows from other themes and prevents the algorithm to classify every dark regions of the image as "rocks in shadow".

Figure 8: Results without (on the left) and with (on the right) prior information about shadows (rocks in red, screes in pink, pasture in yellow, water in blue)

5.1.3 Prior information from the relief and CLC2000 The results obtained without introducing prior information in the classification process are very noisy and bad with many confusions (such as dark pasture and forest, or glaciers and light screes...). The introduction of prior probabilities considerably improves the classification results.
The balance between the different information sources has been tested too. Good results (see table 1) have been obtained with the following weights : 1 for image information, 0.75 for relief information and 0.25 for CLC2000 information (and 1 for shadow probability). A too important strength given to CLC2000 knowledge leads of course to too generalized results.
Concerning CLC2000, several prior probability models have been tested too and a convenient model for the two test zones has been found.

5.2 Final results and evaluation

The results were visually (on the whole image) and numerically (on smaller test zones in the image) evaluated. Numeric evaluation consists in computing confusion matrices by comparing test data captured by an operator to the classification result. Nevertheless, it is difficult to evaluate the obtained results since even a human operator can find it hard to discriminate landcover themes in some parts of the test zones. Moreover, concerning the particular case of glaciers, they can be covered by screes and therefore classified as screes (by the algorithm and a human operator).

Concerning the first test zone, obtained results are equivalent to the ones obtained by the previous study with little improvements in particular parts of the zone. A score of almost 67% well classified pixels (after aggregation of shadow/non shadow classes) among the test data has been obtained (see table 1). For comparison, a score of less than 55% well classified pixels has been obtained without prior knowledge. These results could seem quite bad but the part of the image where those zones are located is very difficult to classify, even for a human operator (see figure 9). Besides, the obtained results are sufficient for the new base map purposes. On the second test zone, better results have been obtained since almost 90% of the pixels of the test data have been well classified (table 1, figures 10, and 11). In this case, it must be said that test data zones are scattered in the whole image and are not so many as in the Alps zone. These better scores are also explained by the fact that there are less problems with the radiometry of the digital orthoimage used here than with the radiometry of the scanned argentic orthophoto available on the Alps' test zone. In addition, the *NDVI* channel is available here and is usefull to discriminate vegetation and non vegetation regions. Nevertheless, prior information has been necessary to prevent many misclassifications and to limit noise (for instance very small rocky zones in a wide pasture zone).

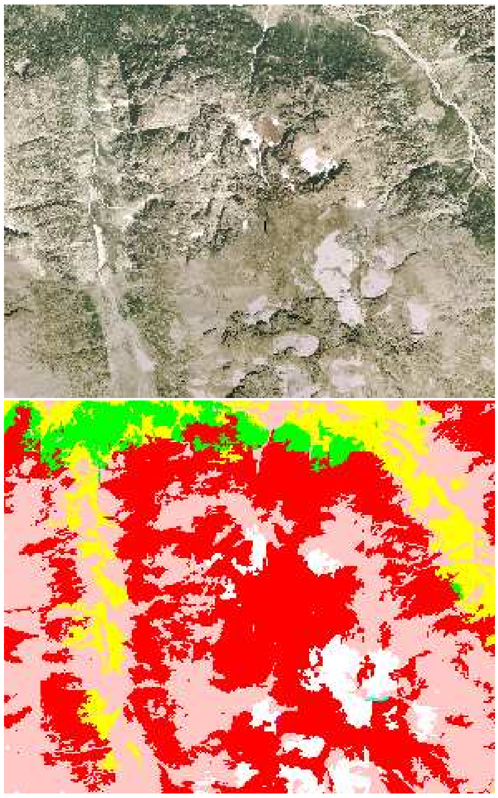

Figure 9: Example of classification in the Alps'test zone (rocks in red, screes in pink, pasture in yellow, forest in green, glaciers in white)

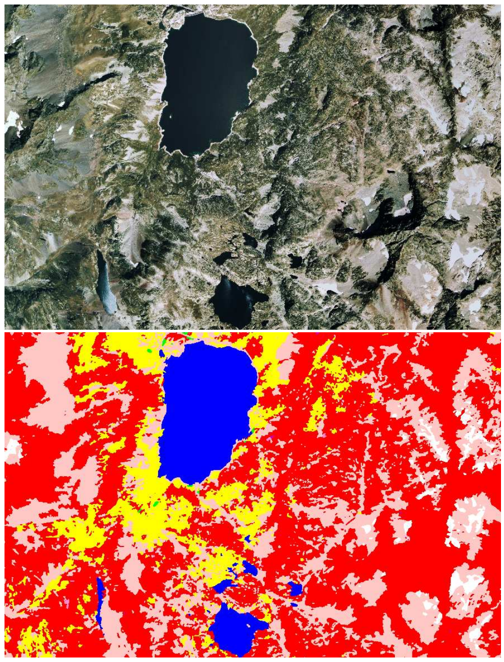

Figure 10: Example of classification in the Pyrenees'test zone (rocks in red, screes in pink, pasture in yellow, forest in green, glaciers in white, water in blue)

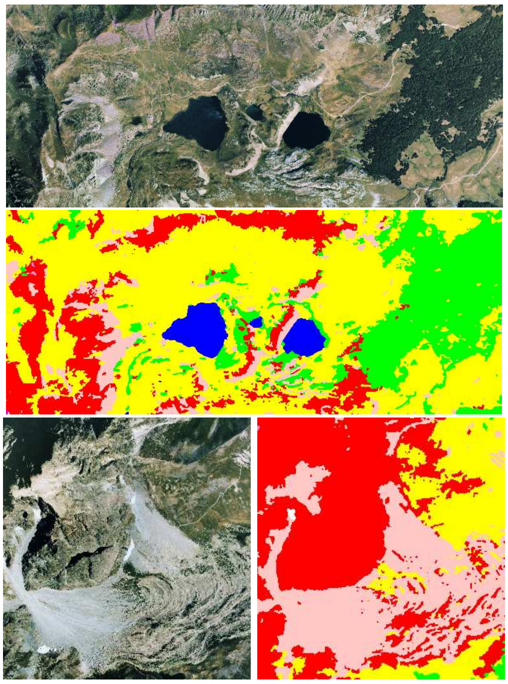

Figure 11: Example of classification in the Pyrenees'test zone (rocks in red, screes in pink, pasture in yellow, forest in green, glaciers in white, water in blue)

Table 1: Results obtained on the test zones (in %) with prior information: *us-ac* is the user accuracy and *pr-ac* is the producer accuracy.

	Pyrenees		*Alps*	
	with prior information			
	us-ac	*pr-ac*	*us-ac*	*pr-ac*
Water	100,0	76,4	/	/
Forest	89,0	95,8	81,9	65,2
Pasture	96,3	85,1	71,1	52,2
Rocks	71,0	87,2	76,4	69,9
Screes	88,0	83,1	54,7	73,3
Glaciers	98,3	72,2	58,6	69,5
Well classified pixels	87,4%		67,0%	
	without prior information			
Well classified pixels	75%		55%	

A visual evaluation has not revealed important errors on both test zones, and most of the regions of the classification have cartographic meaning (which is important in our mapping context).

5.3 Computing time

The tests have shown that the segmentation of orthoimages corresponding to a French base 1/25 000 map would take almost 6 hours with a single technical computer. The classification step would last almost 2 hours. It must be said that the initial 50cm resolution image has been previously downsampled to a 2m resolution image before the different computations. This allows to reduce the computing time and to obtain better segmentation results.
However, the computing time can yet be reduced, since before the start of the downsample - derived channels computation - segmentation - classification steps, the whole image is splitted into smaller images that are treated alone before being merged at the end of the computations. As a consequence, these small images can be treated in parallel on a cluster.

6 CONCLUSIONS AND FUTURE WORK

The obtained results are suitable for the new base 1/25 000 map's purposes since they are as precise and as generalized (after a local fusion of the smallest remaining regions without cartographic meaning).
The tests have shown that the introduction of external information from the relief or another database is necessary and to what extent this improves the result. They have also allowed to test how it is possible to use a more generalized database with a different legend, such as CLC2000 in the classification process. Tests have also proved that correcting the shadows is not necessary since dividing each class into "shadow/non shadow" subclasses is sufficient even though prior knowledge about the shadows'localization improves the results.
The method presented in this paper will now be tested on a new and more precise DTM in order to know to what extent it improves the results. It will also be tested on a new test zone (in the Alps) where all the landcover themes of the classification are present and where new 4-bands orthoimages (captured by a digital camera) are available.

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