IMAGE-TO-MAP CONFLICT DETECTION USING ITERATIVE TRIMMING : APPLICATION TO FOREST CHANGE

Radoux, J. and Defourny, P.

Department of Environmetrics and Geomatics
Université catholique de Louvain
Croix du Sud, 2/16, B-1348 Belgium
(Julien.Radoux,Pierre.Defourny)@uclouvain.be

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ABSTRACT:

Large scale vector databases are valued tools for forest management. It is therefore important to keep these databases up to date and various change detection methods have been designed in this aim. Recently, object-based iterative trimming was successfully used to detect change in temperate and tropical forests. The goal of the present study is to transfer this image-to-image method in an image-to-map application. This study focuses on the detection of clear cuts and forest regeneration areas in a multi-spectral Quickbird image. Various steps were necessary to bridge the gap between this image and the vector database. In order to reduce the effects of residual parallax, the vector database was modified along forest boundaries using the viewing parameters of the satellite. Besides, the image was segmented with a large homogeneity constraint in order to produce ”pure” image-objects. Eventually, the resulting image-objects were automatically labeled using the information from the modified vector database, and the trimming algorithm was run for each forest class. The hypothesis behind iterative trimming is that objects belonging to the same class share similar characteristics (e.g. spectral reflectance). In other words, they belong to the same distribution. The class distribution was estimated using a non parametric method in order to fit to the data even with complex distributions. The chosen method used kernel density estimates to build the probability density function. Outliers were excluded based on a density threshold and the new parameters of the distribution were reprocessed until the all objects are above the new threshold. The resulting outliers included the majority of the discrepancies between the image and the map in the forest areas. About 50 % of the forest regeneration and 100 % of the clear cuts were properly detected. It is a promising way to improve semi-automated map updating because the training dataset is the vector database itself. However, further work is needed to test the method on other land cover types and to move from the detection toward the classification of the discrepancies.

1 INTRODUCTION

Large scale vector databases are valued tools for forest management and Geographic Information System (GIS) have been used in manifold forest application such as forest pest models (White, 1986) or fire management (Lowell and Astroth, 1989). Keeping these database up to date is a real challenge because of the cost of the field surveys in often remote areas and the frequency of change due to exploitation and natural hazards (storms, insects...). Very high resolution remote sensing gives the opportunity to update forest maps at lower costs. Nevertheless, semi-automated processes are still to be develop in order to provide operational tools for change detection.

Change detection algorithms provide valuable tools toward the automation of map update. Broadly speaking, there are two main approaches for change detection : post-classification comparison or change mask classification. In the first case, two images are classified, independently and with the same legend, and the resulting maps are crossed or combined with specific decision rules. This approach suffers from error propagation and misregistration but gives straightforward information about the type of change. In the second case, corresponding pixels or objects of different dates are processed together in order to produce a change mask, most of the time without information about the type of change (Coppin et al., 2004, Lu et al., 2004).

Different image-to-image change detection algorithm have been applied successfully on forest/non forest change. Recent studies (Stow et al., 2008, Hyvönen and Anttila, 2006) used object-based classification (respectively nearest-neighbor and discriminant analysis) with bi-temporal aerial photographs. These methods showed good performance on the dataset but relied on training samples which may be costly to produce. The LTA-SVM algorithm (Huang et al., 2008) used support vector machine (SVM) on automatically selected training based with the assumption that forests were the darkest vegetation type. Unfortunately, this method, appropriate with Landsat images, cannot be applied on very high spatial resolution images because enlightened tree crown pixels are then as bright as other vegetation types. Another approach used iterative trimming on multi-temporal image-objects with the assumption that outliers in the distribution were likely to be forest change (Desclée et al., 2006, Duveiller et al., 2008). This method required a probability threshold to be adjusted, which could be used for the whole images dataset.

Image-to-vector land cover change detection algorithms are less common that the former. Nevertheless, there is a great potential coming from conflation or integration methods, where the information from two digital maps are combined to produce a third map which is better than each component sources (Cobb et al., 1998). Based on matching algorithms, these methods are used for boundary deconflicting (Butenuth et al., 2007) or network registration (Chen et al., 2006) using, e.g., edge detection filter and snakes. Other applications used both image and vector to evaluate forest damages (Schardt et al., 1998), but image classification often remained a necessary intermediate step for conflation. Nevertheless, recent studies achieved automated detection of new buildings based on color information (chrominance) extracted from matching buildings between a vector database and a aerial photograph (Ceresola et al., 2005). A similar approach was used to classify land cover thanks to training areas extracted from the vector database (Walter, 1998), but in this case the presence of discrepancies inside the training dataset and the spectral heterogeneity inside the land cover classes reduced the accuracy of the classification.

This study proposes a hybrid method using image processing and GIS techniques in order to detect discrepancies between a single satellite image and a vector database. The proposed method is applied on change detection in temperate coniferous and deciduous forest stands subjected to regular logging, where most of the discrepancies are due to forest change.

2 DATA AND STUDY AREA

The study area is located in Southern Belgium and covers $40km^2$ of a rural landscape including forests, agricultural land and small villages. The forests in this area are very fragmented temperate forests including a dozen of different coniferous and deciduous species ranging from regeneration to mature (up to 100 years old) stands. It is covered by a Quickbird image and a vector database based on the Belgian National Geographic Institute (NGI) data.

The multispectral Quickbird image was taken in summer 2006 and was provided as a orthoready product. It was orthorectified using the Rapid Polynomial Coefficient provided with the product and a 1/50 000 digital elevation model. The ground control points were located from the vector database and the RMSE of the orthorectification model was around 2 m at ground level. The image was resampled at 2.8 m using a cubic convolution.

The vector database was composed of a 1/10 000 reference database from the Belgian NGI and was complemented by a field survey in 2005. The NGI map achieved 1 m accuracy on non generalized objects. This study focused on pure coniferous and deciduous forests. They were distinguished in two classes on the map and covered about 25% of the total area.

3 METHOD

In this study, the primary assumption is that the vector database is a reliable source of information and that changes occur on limited areas. The detection of the discrepancies between the vector database and the image consisted in three steps. First, the GIS database is edited to account for residual parallax shift (section 3.1). Second, the image is segmented and labeled based on the GIS database (section 3.2). Third, potential outliers are identified using iterative trimming (section 3.3).

3.1 Secondary GIS database

The large scale vector databases from the NGI was produced thanks to the photo-interpretation of aerial photographs complemented with field surveys. Each land cover type is clearly described in terms of actual content and delineation characteristics. The representation of the objects in the database is also constrained with some cartographic rules such as minimum mapping unit or edge generalization. Remote sensing imagery gives a snapshot of the reality that differs from a categorical map in several aspects : (i) boundaries are not generalized and are sometimes fuzzy, (ii) a given class may have different phenology due to, e.g., vegetation seasonality or thematic generalization, (iii) some objects are hidden by others and some edges suffer apparent shift due to parallax and shade effects. Parallax effects can be corrected on the image when the orthorectification uses a digital surface model (DSM), but this creates gaps where there was no visibility, which are commonly filled with neighboring pixel values. Instead of this, the image to map comparison was performed based on a secondary vector database where the shadows and the parallax effects were modeled(equation 1). This simple trigonometric model used the mean satellite zenith and viewing angles to predict parallax, which is precise enough with regards to the spatial resolution of the satellite image. The apparent shift S was calculated in the direction of viewing azimuth angle based on stand height (H) and viewing zenith angle (VZA). Shadows were modeled the same way using the solar angles instead of viewing angles. Spatial decision rules were then used to combine the different layers consistently with the visibility from space. For instance, shadows were hidden by the shifted tree crowns and buildings but occluded other land cover types at ground level. This created a secondary GIS database used in section 3.2.

$$S = tan(VZA) * H \tag{1}$$

3.2 Image pre-processing

The labels of the GIS database were used as *a priori* information in order to classify the Quickbird image. To do so, the orthorectified Quickbird image was segmented using Definiens software (Baatz and Schäpe, 2000) with small scale parameters (30) and 20% of this threshold allowed to the compactness. These parameter were found as a good compromise between the spectral coherence and the representativity of the image-objects within each land cover class. However, the method is not very sensitive to slightly different values. After segmentation, each image-object was labeled thanks to a majority rule on the GISdatabase and the mean spectral values were extracted for each band of the image.

3.3 Multivariate iterative trimming

Trimming consists in truncating a distribution from its least probable values that behave like outliers. The common purpose of this procedure is to improve the estimates of the parameter characterizing a given distribution, such as sample mean and variance in the case of Gaussian distribution (Kotz et al., 1988). As the aim of this study is to identify discrepancies between the map and the image, trimming is used to screen image-objects which are not likely to be part of the real class distribution. As the estimates of the distribution are influenced by the outliers, trimming is performed until there is no more outliers. The estimates of the distribution are thus updated at each iteration.

Contrary to the distribution of image differences, as used by (Desclée et al., 2006), the distribution of spectral values in land cover classes cannot be parameterized with only a few parameters because complexity of the land cover patterns. Indeed, a single class may contain several sub-classes. For instance, *Picea sp.* and *Larix sp.* stands are both labeled as "coniferous" but do not have the same reflectance. Furthermore, temperate deciduous forests are textured at the resolution of Quickbird multispectral sensors (2.8 m). As the segmentation algorithm was mainly based on spectral values, objects belonging to this class were grouping crown pixels or shadow pixels together, so leading to bi-modal distribution of the image-object pixel values. A non-parametric probability density estimate, kernel density estimate (Silverman, 1986), was therefore selected because it does not require any assumption on the shape of the distribution and is hence adaptive. Gaussian kernels were selected for their good smoothing properties due to their open domain. For each iteration, the data were whitened and the bandwidth was optimized using the Fukunaga method (Fukunaga, 1972) (equation 2) .

$$f(x) = \frac{(detS)^{-1/2}}{nh_{opt}^d} \sum_{i=1}^{n} k\{h_{opt}^{-2}(x - X_i)^T S^{-1}(x - X_i)\}, \tag{2}$$

where S is the covariance matrix, d the number of dimensions, n the number of observations and $k(x^T x)$ a Gaussian kernel. h_{opt}

is the optimal bandwidth given by equation 3. The chosen kernel smoothing method is the least expensive in terms of computation time and its main disadvantage is a risk of oversmoothing in case of large distribution tails. It therefore suits an iterative trimming, which requires several calculation of the optimal bandwidth and removes distribution tails.

$$h_{opt} = \{4/n(d+2)\}^{1/(d+4)} \tag{3}$$

The selection of outliers relies on a probability threshold α, which is the only parameter that users need to tune. Values of 2.5, 5 and 10 percent were used in this case study. The density values below which the integral of the probability density function (*pdf*) was smaller than α were considered as outliers. For numerical reasons, the integral was discretized so that the density threshold was calculated at the zero of equation 4 for t.

$$\left\{ \sum_{\{x \in \mathbb{R}^d | f(x) \geq t\}} f(x)\Delta x \right\} - 1 + \alpha \tag{4}$$

3.4 Accuracy assessment

The validation of the results was performed based on the comprehensive visual interpretation of the 6000+ objects labeled as "coniferous" or "deciduous". For the sake of the analysis, discrepancies between the map and the image were classified in 3 categories : clear cuts, regeneration and wrong class (deciduous labeled as coniferous and reverse). Image-objects representative of the class they belong to were labeled as "typical". Besides, the shaded crowns and small forest gaps were labeled as "shadows". Eventually, image-objects embedding both representative pixels and discrepancies were labeled as "mixed" when the least frequent type occurred on more than 25 % of the object area. Table 1 summarize these values for each land cover class.

	Coniferous [ha]	**Deciduous [ha]**
Typical	213.0	647.6
Shadows	1.9	25.4
Clear cut	2.2	9.6
Regeneration	41.0	0.4
Wrong class	8.4	0.1
Mixed	10.7	13.2

Table 1: Area of the object categories used for the validation

4 RESULTS

Image-object produced by the segmentation of the image were automatically labeled based on the secondary vector database. The different steps of the process are presented on figure 1. As shown in table 1, mixed-type objects occurred on both forest types. They covered 4 % of the forest areas labeled as coniferous, and 2 % in the case of deciduous forest. These mixed-type objects were identified as discrepancies only for large values of α and were mainly located at the interface between forests and crop fields. It is worth noting that the thematic accuracy of the vector database was very good. Most discrepancies were caused by forest exploitation and only a few percentage was due to confusion between deciduous and coniferous. There was no confusion with other land cover classes in this case study.

The change detection errors (Biging et al., 1998, e.g.) were computed for the three values of α and each forest type (Tables 2 and

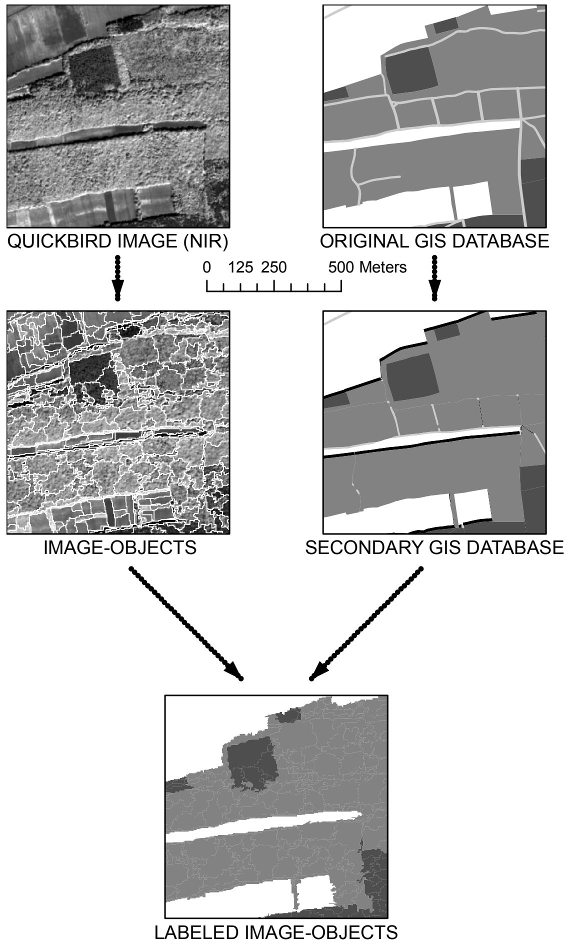

Figure 1: Results of the automatic labeling process. Left figures are subsets of the image pre-processing and right figures show the creation of the secondary GIS database. The resulting majority map is shown at the bottom.

3). By construction, the number of outliers increased when the α values increased. The detection accuracy of discrepancies was therefore better when α was large but this created more commission errors (overdetection). For instance, the detection of forest regeneration increased gradually from the use of small α toward larger ones. However, it remained insufficient for the coniferous forests and was associated with smaller detection accuracy of the unchanged objects (in other words, more commission errors). Clear cut detection was nearly perfect except with $\alpha = 0.025$ in the coniferous forest. Eventually, the method was unable to detect the small coniferous patches in the forests labeled as deciduous and the opposite was also very poor.

	α = 0.025	**α = 0.05**	**α = 0.1**
Typical	100	98	95
Shadows	100	90	85
Clear cut	51	100	100
Regeneration	0	13	28
Deciduous	1	15	51
Mixed	3	59	72

Table 2: Class based detection accuracy for objects labeled as coniferous forests

5 DISCUSSION

The proposed method is promising because of its ability to adjust on different land cover types in order to automatically de-

	α = **0.025**	α = **0.05**	α = **0.1**
Typical	100	95	86
Shadows	99	91	67
Clear cut	100	100	100
Regeneration	47	89	100
Coniferous	0	0	0
Mixed	24	77	93

Table 3: Class based detection accuracy for objects labeled as deciduous forests

tect discrepancies with a high detection accuracy and acceptable commission errors. Unfortunately, it is limited by the facts that discrepancies must be scarce and different from the main class. If the frequency of a given discrepancy type is too high, like for regeneration in coniferous in this study, their probability density remains above the threshold and the use of alternative approaches is necessary. When the discrepancies are similar to the main class, other characteristics may be used. However, the total number of characteristics has to remain relatively small to avoid problems when computing the *pdf*.

As often with natural resources, producing a crisp classification of discrepancies with typical forests is useful for decision making and easy to interpret, but is not coherent with the field reality. Whereas clear cuts are unambiguously defined on the field, there are different types of regeneration and there is a gradual change between clear cut and mature forest stands. The outliers detection also gives additional information on the reliability of the detection, namely the probability density and the number of iteration before the object was excluded, which could improve the interpretation of these results.

While the iterative trimming could be used either with pixels or with objects, using objects has several advantages: (i) it reduces the computation time, (ii) it is not sensitive to small misregistration errors and (iii) it reduces the intra-class heterogeneity, which improves the detection of outliers. However, the use of spectral-based segmentation algorithm did not reduce the heterogeneity in deciduous forest as shaded and enlightened crowns formed distinct image-objects (figure 2). On the other hand, reducing the spectral component in the segmentation algorithm would produce more undesired mixed object which are also difficult to handle. The development of texture-based segmentation algorithm may thus improve the accuracy of the overall trimming process.

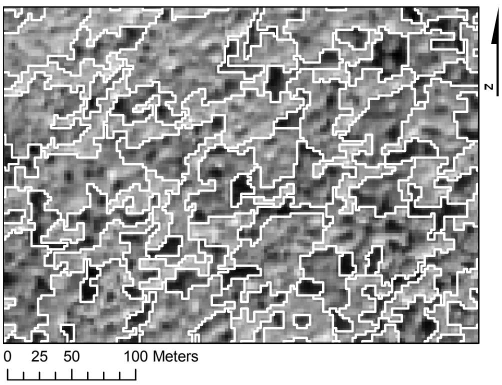

Figure 2: Details of a typical deciduous mature stand in Belgium illustrating the heterogeneity of the object mean values in near infra-red (NIR). Spatial resolution is 2.8 m.

6 CONCLUSION

The proposed method was able to extract useful information for forest managers based on a single satellite image and an existing GIS database. The main advantages of the method are its flexibility and easy tuning capability. Its main disadvantage is its limited capabilities in case of high frequency discrepancies.

Further work is necessary to classify the results of the outlier detection, based on the automatically extracted information from the typical classes. Combined with comprehensive discrepancy detection in each land cover type of the GIS databse, this would help to reduce the costs of map update.

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