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DETECTING MAN-MADE STRUCTURE CHANGES TO ASSIST GEOGRAPHIC DATA PRODUCERS IN PLANNING THEIR UPDATE STRATEGY

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ABSTRACT:

Topographical data producers are currently confronted with the need for a faster **updating** method. Indeed, this need was assessed at the first stage of the ARMURS(*) project by surveying several Belgian and international mapping agencies. The aim of the project is to build a demonstrator to assist data producers in planning the update of their topographic database more efficiently relying on remote sensing images, together with socio-economic and demographic data. At a **regional scal**e, the man-made structure changes extracted by the ETATS module on a SPOT5 panchromatic image will be fused with a change analysis on socio-demographic data. At a **local scale**, as regards areas of predicted changes, the older databases are compared with recent very high-resolution satellite or aerial images in order to detect changes in man-made structures. Changes are detected by comparing an object-oriented classified VHR image to a simplified version of the old database. This object-oriented approach consists in a segmentation followed by a classification. Three **segmentation** methods (Watershed Assembly, Graph Cut, Mean Shift) were implemented and compared to the one of a commercial software (Definiens); indices were proposed to assess the quality of these segmentations. Features are selected either according to a visual interpretation formalised into an interpretation key, or by quantitative methods such as the forward Jeffries-Matusita distance or mutual information criteria (mRMR); selections are compared. By using a common framework (images, training set and validation set), existing **classification** methods available in Definiens and in R are compared. A final step of **change detection** gives us preliminary results.

1. INTRODUCTION AND OBJECTIVES

1.1. Introduction

Detection and identification of man-made structures on remote sensing images is essential in many applications, such as land and urban planning, environment management, climate change, water management, risk management, disaster monitoring and mitigation, infrastructure development... (Carleer and Wolff, 2006). Since the middle of the 80's, developed countries are producing numerical topographic databases. The need for update is challenging because it is too expensive to cover the whole country with the same production method and at the same time to respond to the demand of a frequent update.

Since the years 2000, very high resolution (VHR) sensors such as IKONOS, QuickBird, and recently GeoEye have been launched. Their submetric spatial resolution comes nearer the resolution of aerial photography, generally preferred by the mapping agencies when they only had the choice between high-resolution sensors and aerial photography (Stephenne *et* al, 2003). Indeed, national mapping agencies generally update by photogrammetry (Holland *et* al., 2006; Walter, 2004; Bailloeul *et* al., 2003; Knudsen and Olsen, 2003; Gianinetto, 2008), which is tedious and time consuming. Change detection has been widely studied in remote sensing (Coppin *et* al., 2004), and some research has been done to improve, thanks to those techniques, the update of topographical database (Knudsen and Olsen, 2003; Holland *et* al., 2006; Gianinetto, 2008; Carleer and Wolff, 2007). The old database can be used in the change detection process as an a priori knowledge either as training area for the region-based classification by supervised maximum likelihood (Walter, 2004), or to constrain the segmentation process (Bailloeul *et* al., 2003; Carleer and Wolff, 2007). The constraint segmentation corresponds to the manual practise, where in fact, the expert uses a comparison to the old database to detect changes in the area.
Until now, there exists no commercial semi-automatic tool to detect changes for planning the update of topographical database.

1.2. Objectives

The general objective of the ARMURS project is to develop a demonstrator to assist data producers in updating more efficiently their topographic database by using state-of-the-art image processing and statistical analysis techniques. At a regional scale, such as a HR scene, the objective is to merge the results from the ETATS module, previously developed (Lacroix *et* al., 2006), with a statistical analysis in order to highlight areas

(*) ARMURS: Automatic Recognition for Map Update by Remote Sensing, http://www.armurs.ulb.ac.be/index.php/Main_Page of change in man-made structures (MMS), and to predict their localisation. At a local scale, such as a VHR scene, for areas of predicted changes at the regional scale, the older database is compared with features extracted from recent VHR images in order to detect and locate MMS changes.

Section 2 presents the user needs gathered at geographical agencies or institutes while section 3 describes the studied areas. Change detection for man-made structures (MMS) at the regional scale is detailed in section 4 where the ETATS project, the statistical analysis and the fusion of both are presented. Section 5 presents change detection at local scale for the MMS, through segmentation (Definiens, Mean-Shift, Graph-Cut, Multi-Watershed Assembly, assessment of the segmentation methods), feature selection (visual interpretation key, quantitative feature selection), and classification methods (Definiens, others classification methods) retained in the ARMURS project. In section 6, change detection from the commercial software Definiens is described. The ARMURS demonstrator is presented in section 7. Mention that results are shown in appropriate sections (and not in one specific section). Section 8 concludes the paper.

2. MAPPING AGENCIES UPDATE NEEDS

The needs of Belgian and European topographical database producers have been assessed through a survey. The surveyed agencies are the Belgian National Geographic Institute (NGI-B), the Brussels Regional Informatics Centre (BRIC), the Flemish Geographic Information Agency (AGIV), the Walloon Ministry of Equipments and Transport (MET), the French National Geographic Institute (IGN France), the Ordnance Survey (OS) and the Bundesamt für Kartographie und Geodäsie (BKG).

It appears that the used techniques in the update process, mostly areal photogrammetric restitution and ground survey, are tedious, too slow and expensive. In fine, those agencies wish to apply a continuous update for instance by the centralization of the as-build plans and of the land surveyor's reports after a standardization of the way to make these reports which is not currently effective. This update process had to be reorganized to allow a better update frequency especially for objects like buildings and roads.

Another challenge for those producers is to focus on the change areas rather than apply a systematic update of the whole territory. It would be particularly useful to identify the no-change areas where there is no need to update. Change detection is then a key issue for the topographical database producers.

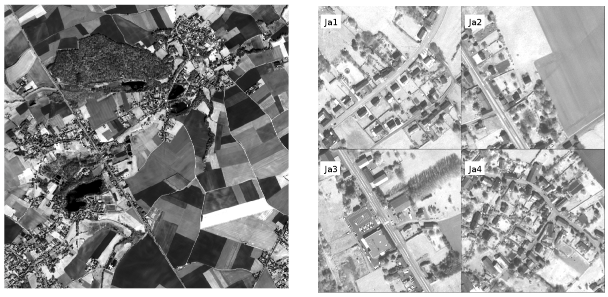
The trend emerges toward differentiated update strategies according to the objects and the areas; buildings and roads on the one hand and urban areas on the other hand being updated more frequently. Moreover, some agencies, such as OS, do not map their land at a constant scale; urban areas are mapped at a more detailed scale than forested ones.

3. STUDIED AREAS

At the regional scale, the study area covers a SPOT scene of 60*60km including Brussels and various landscapes (urban, periurban and rural).

The local study area (3km*3km) is located in the rural zone of Jodoigne (Belgium). For the preliminary segmentation works, four smaller areas were delimited (cf. Fig 1) to represent the different landscape.

At local scale, we used the 4 m spectral bands and the 1 m panchromatic band of the April 24 2008 IKONOS. Two databases are used. A first database (DB0) is extracted from the 1 : 10 000 database of the Belgian National Geographic Institute; the database was simplified in 5 classes (built-up, roads, vegetation, bare-soils and water), DB0 was updated by visual interpretation of the 2008 VHR imagery to produce DB1.



(a) the full Jodoigne area

(b) Jodoigne areas: (Ja1) sparsely built-up, (Ja2) sparsely built-up with trees and fields, (Ja3) commercial, (Ja4) built-up (i.e. village centre)

Figure 1: Four areas selected in Jodoigne

4. MMS CHANGE DETECTION AT REGIONAL SCALE

The regional approach for MMS change detection is based on two different kinds of information: High Resolution images (HR) (on degraded aerial photos) and socio-economic and demographic statistics. These HR images are processed by the « ETATS » module, developed in another project for the Belgian National Geographical Institute (NGI), to detect coarse MMS changes (Lacroix *et* al., 2006). Socio-economic and demographic statistics are recorded in the census and administrative databases. Their use relies on the hypothesis that MMS changes are related to the socio-eco-demographic evolution as it is represented in these statistics. HR images exhibit a quite detailed view of MMS changes whereas statistics are free of charge. Therefore, the ETATS and socio-eco-demographic statistics are considered as complementary and are fused to predict MMS changes.

4.1. ETATS

The ETATS module was developed for change detection for the Belgian National Geographical Institute databases of building and roads thanks to aerial or satellite images (spatial resolution from 2.5 to 5m) (Lacroix *et* al., 2006). Texture measures are used to distinguish man-made structures pixels from the rest. Thoses pixels are then compared to a database to derive a map with 4 classes: « no urban change » (green), « new urban area » (yellow), « error in the database/bad detection/destruction » (red), « area out of interest » (black).

As a first attempt, the ETATS module was applied to a western zone of the Brussels Region and neighbourhood (8x5km). This area, covering Anderlecht, was selected because it contains dense urban and rural areas in a zone affected by recent changes (cf. Fig. 2). The aerial image (8km x 5km) at 0.5m resolution has been downsampled to 2.5m to suit the data resolution acceptable for ETATS. The map automatically delivered by ETATS (cf. Fig. 2) was evaluated relatively to a ground truth realised at the NGI. Concentrating on large buildings or large built up areas (minimum 3000m2), the success rate for detecting new built-up areas achieved 77%. Wrong detection of roads mainly concerned those ones occluded by trees.

Figure 2: Aerial image from Anderlecht at a resolution of 2.5m, 8km x 5km
(Legend: « no urban change » (gray), « detected new urban area » (yellow), « ground truth for the new urban area » (pink), « area out of interest » (other))

4.2. The statistical approach

We also propose another change detection approach based on statistical learning analysis of socio-demographic data. Like all learning processes, several steps are needed to obtain an accurate predictive model. Due to the potentially high number of statistics available for each region (e.g., demographic, economic or geographical information), the learning process must start by a feature selection algorithm. The link between the socio-demographic data and the change could be highly nonlinear and must be estimated by nonlinear modelling without overfitting. This statistical learning approach was first tested on one hundred sectors of the Brussels region where the objective was to predict the probability of change in the soil impermeability. The first results show good overall accuracy but we still observe a high underestimation of the change in regions having many wooded area or parks.

4.3. Fusion of ETATS and the statistical approach

Both ETATS and the statistical approach return predictions of change but at different levels. ETATS returns a prediction at the pixel level while the statistical approach makes predictions for regions. We propose two solutions to merge both these predictions: either aggregate the prediction of ETATS for each region or distribute the prediction of the statistical approach on each pixel of the region. However, the final merge prediction will be obtained by weighted averaging of these predictions.

5. MMS CHANGE DETECTION AT LOCAL SCALE

At a local scale, for areas of predicted changes at the regional scale, the older database is compared with features extracted from recent VHR images in order to detect and locate MMS changes. An object-oriented approach was adopted because it allows i) to overcome the salt and pepper effect (Carleer *et* al., 2003), ii) to obtain a higher level of object identification (Civco *et* al., 2002; Im *et* al., 2008; Laliberte *et* al., 2004; Niemeyer *et* al., 2003; Walter, 2004), iii) to characterize the regions not only according to their spectral values, but also to their shape, size, texture, pattern, context, association (Lillesand and Kieffer, 1994), …. In such an approach, a segmentation step precedes the classification process.

5.1. Segmentation

Three segmentation algorithms (Multi-Watershed Assembly contour-based, and Mean-Shift and Graph-Cut region-based) are compared to the one included in the Definiens software. Most methods were adapted to include a priori knowledge; indeed, the objects of the old database (DB0) are included within the segmentation process. This knowledge allows to train the classifier as changes are few and to constraint segmentation. Moreover, it decreases the number of small uninteresting polygons of change (Carleer and Wolff, 2008). The comparison of the results is achieved quantitatively in order to diminish the human interaction to assess the quality of the results.

5.1.1. Definiens (DEF)

The Definiens software is commonly used for image segmentation and classification purposes. According to the User Guide (Definiens, 2007), it merges pixels or existing image objects by minimizing the average heterogeneity and maximizing their respective homogeneity. Three parameters have to be fixed: (i) the scale factor; (ii) the shape factor (defining the relative importance of the shape to the colour); (iii) the compactness (the relative importance of the compactness to the smoothness). The used scale parameter was 25, the shape factor 0.6 and the compactness 0.8. Results are shown on figure 3(a).

5.1.2. Mean-Shift (MS)

Within the feature space, the mean shift (Comaniciu and Meer, 2002) operates by estimating in an iterative way the local maxima of the underlying nonparametric feature distributions. The mean-shift was applied on the red, green and blue (RGB) bands on the aerial image in Anderlecht (Brussels). The spatial radius was 7 pixels and the spectral radius 20 levels in the RGB space. Results are shown on figure 3(b).

5.1.3. Graph-Cut (GC)

Segmentation by graph-cut acts by minimizing an energy function composed of two terms: i) the likelihood of the data measuring the disagreement between an energy function and the observed data (« seed »), ii) the smoothing term evaluating the coherence with the neighbourhood (Kolmogorov and Zabih, 2004). Applied to the pixels, a labelled image is obtained by merging connected pixels linked to the same « seed » (Boykov and Jolly, 2001). The four images (in panchromatic band in Jodoigne area) are gathered into a mosaic (cf. Fig. 1b) in order to train the different classes (« built-up », « roads »,

« vegetation »). Histograms for each class have been calculated into the mosaic image constrained by the old database, making the hypotheses that the modifications with a recent database are weak. Four seeds are selected: (i) the modal value for the roads class; (ii) the modal value for the built-up class; (iii) The modal value and a second maximum for the intermediate vegetation class. Results are shown on figure 3(c).

5.1.4. Multi-Watershed Assembly (MW)

The watershed transform is well known to detect borders and create closed contours (Beucher and Lantuéjol, 1979). Its extreme sensitivity may lead to over-segmentation. This problem increases with the image resolution. The marked watershed transform limits the number of obtained basins, requiring the definition of adequate marks. Another way to limit over-segmentation is to keep only stable basins with respect to perturbations of the data (i.e. use random marks) (Debeir *et* al., 2009; Noyel et al., 2007). Furthermore, this method allows the injection of prior knowledge by forcing gradient at the database available borders.

Applied on panchromatic, two kinds of parameters are associated with this method. The firsts are related to the noise injected both in the gradient random perturbation intensity and random marks density. The seconds are related to the granularity of the obtained segmentation by tuning the sensitivity to robust border detection (i.e. the number of time must belong to a border in order to be considered as a stable border). Of course, because the method modifies the gradient image used, it allows the injection of prior knowledge by forcing for instance the gradient along the database available borders, in order to recall those borders in the segmentation. Results are shown on figure 3(d).

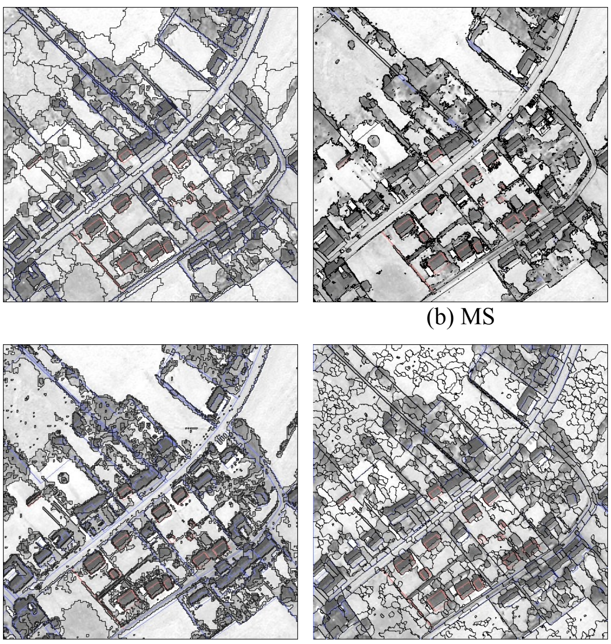


Figure 3: Results of the differents methods of segmentation

5.1.5. Comparison and assessment of the segmentation methods

Two main segmentation defects are over-segmentation and under-segmentation. The latter is more serious since borders are definitely lost for the following processes. The updated version of the old database (DB1) being the reference, the over- and the under-segmentation are assessed by computing the number of added borders and missed borders. The best segmentations minimize both indicators.

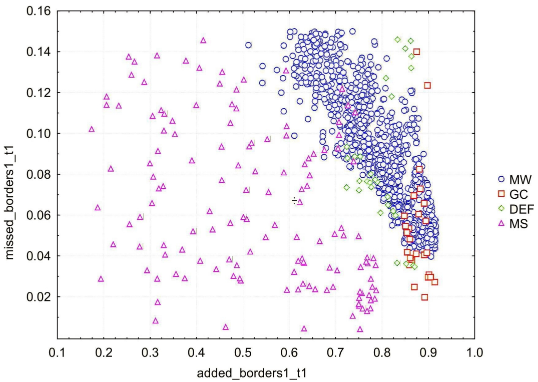


Figure 4: Plot of the percentage of added borders against the percentage of missed borders.

The graphical comparison of the segmentation methods shows that all of them have few missed borders but only the Mean-Shift method reaches the best compromise (cf. Fig. 4).

5.2. Feature selection

After the segmentation procedure, the regions may be characterised according to their spectral characteristics, but also to their shape, size, texture, pattern, context, association. Therefore, when considering the high number of parameters in the classification process, a step of variables selection is necessary to avoid overfitting.

In this paper, feature selection is guided by a visual interpretation formalised into an interpretation key and a quantitative approach according to the Jeffries-Matusita distance (Richards and Jia, 1999) and the mRMR (Peng *et* al., 2005). The comparison of the results aims at answering the following question: « Do the features selected by visual interpretation correspond to those coming from the quantitative selection methods? ».

5.2.1. Visual interpretation key

The visual interpretation key is built upon the panchromatic band, a true and a false colour composites, a NDVI and the near infrared band. The segmented regions obtained from Definiens are also used in order to characterize their size and shape. The segments obtained from Definiens have been chosen instead of the ones from the best segmentation (Mean-Shift) because i) the Definiens program integrates the old database and ii) a lot of features can be extracted easily. The NDVI is selected to differentiate vegetation. If NDVI is low, roads are discriminated from bare soil, built-up, water, and shadow, using others features such as shape, colour and texture. For example, the roads are white on the true colour composite, but the built-up too. On the false colour images, roads are in cyan, but so are the bare soil and built-up areas. Among the segmented regions from Definiens, roads have an elongated shape, which is not the case for the built-up. Therefore, the association of the elongated shape and the white colour is used to discriminate the roads. The other distinctions are formalised by the same principle. Once the visual identification key is built (cf. Fig. 5), spectral, morphological and textural features, the 67 features are selected and computed for all segments (regions coming from the segmentation) in order to highlight the various classes.

<table>
<tr><td colspan="4">NDVI high</td><td>Vegetation</td></tr>
<tr><td rowspan="8">NDVI low</td><td rowspan="2">Elongated shape</td><td colspan="2">White (true colour)</td><td>Road</td></tr>
<tr><td colspan="2">Brown (true colour)</td><td>Bare soil</td></tr>
<tr><td rowspan="3">Parallelo-gram shape</td><td colspan="2">Dark (Panchromatic)</td><td>Shadow of a built-up</td></tr>
<tr><td rowspan="2">Light tone (Panchro-matic)</td><td>Low texture</td><td>Built-up</td></tr>
<tr><td>High texture</td><td>Bare soil (parking)</td></tr>
<tr><td rowspan="3">Irregular shape</td><td colspan="2">Cyan (false colour)</td><td>Bare soil</td></tr>
<tr><td rowspan="2">Dark (false colour)</td><td>High texture (Infrared)</td><td>Shadow of vegetation</td></tr>
<tr><td>Low texture (Infrared)</td><td>Water</td></tr>
</table>

Figure 5: Table of the visual interpretation key

5.2.2. Quantitative feature selection

Techniques which estimate non-linear dependencies from multidimensional data are vulnerable to ill-conditioning and over-fitting (Fukunaga and Keinosuke, 1990). Having recourse to feature selection techniques is a typical solution which at the same time provide a useful insight to the analyst about which variables play an important role on the classification. Two feature selection methods are used. The first one searches the best subset of input variables which maximizes the JM (Jeffries-Matusita) distance - based on the Bhattacharyya distance. The second feature selection algorithm is called mRMR (Minimum Redondance and Maximum Relevance) and is based on information theory techniques. Both of them are sequential forward selection methods using two different accuracy measures. Ten features have been chosen to avoid the decrease of the balanced accuracy occurring with more features.
With the mRMR method, more textural features are selected, whereas in the JM distance method, spectral features are highlighted. Note that for both feature selection algorithms, the variables Length/Width, NDVI, and GLCM Entropy were selected in the first stages, and thus seem to be good variables for prediction. Among the variables selected from the visual interpretation key, three of them have been selected by the feature selection process.

5.3. Classification

The classification consists in finding the type of a segment (i.e. water, road, blank, buildings and vegetation).

The segmentation process has generated 39974 segments. This set is first randomly split into two equal parts: a test set and a training set (not entirely used in Definiens). All the learning process is done on the training set (using DB0) and we use the test set (using DB1) to compute the overall accuracy (Congalton, 1991), the KAPPA statistic (Congalton, 1991) and the balanced accuracy (Melvin *et* al., 2007).

5.3.1. Definiens

To evaluate the potential of the proposed classification algorithms, a comparison with the results obtained with the commercial software Definiens has been used. In this study, both thresholds and Nearest Neighbour classification have been used with features representative of different types (colour, shape, texture, relation to the neighbourhood) from the visual selection as well as the type in the outdated database (DB0).
Three major problems appear in the classification and influence the quality assessment. First, crops, classified as vegetation in the DB, are not yet covered by vegetation causing large amount of bare soil on previous vegetation areas. The second problem is due to the occlusion of roads or water bodies by vegetation. The third one is the heterogeneity of the garden class: this class was generalised as vegetation in the database but involves bare soils and small constructions too. Those problems produce in this case a weak accuracy: KAPPA (0.41), overall accuracy (0,71), balanced accuracy (0,51). A solution to overcome those problems in the framework of change detection will be proposed thereafter.

5.3.2. Others classification methods

This section describes the experimental design for classification using the statistical software R (Manual R, 2007).
In our learning set, the output of the samples is highly unbalanced (i.e., 80% of the samples is vegetation) and this makes prediction difficult. We use a boosting process in which fifteen models are built with balanced re-sampled learning sets and a prediction is made after a majority voting process. We apply this boosting process with four types of models: a Random Forest, a Naive Bayes Classifier and an SVM with a linear and a radial kernel.
Figure 6 shows the evolution of the balanced accuracy in case of mRMR which is better than the JM results. Note that the best predictions - according the balanced accuracy - were done by a Random Forest using 40 variables selected by mRMR. The KAPPA, the overall accuracy and the balanced accuracy equal respectively 0.53, 0.78 and 0.71.
Note that the three scores are better for the traditional methods tested in R than for the Definiens classification.
The Random forest incorporates a feature selection process and the SVM is known to be insensitive with the increase of the input dimensionality, unlike the Naïve Bayes This explains why the accuracy of the Naïve Bayes decreases after some variables, while the two others maintains an increase and stabilization.

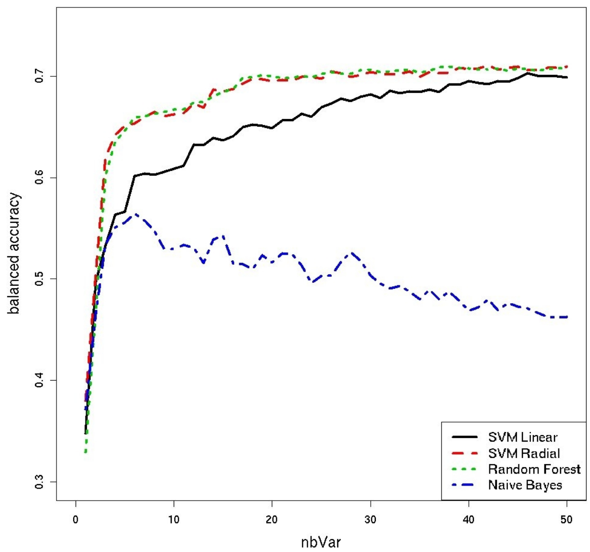
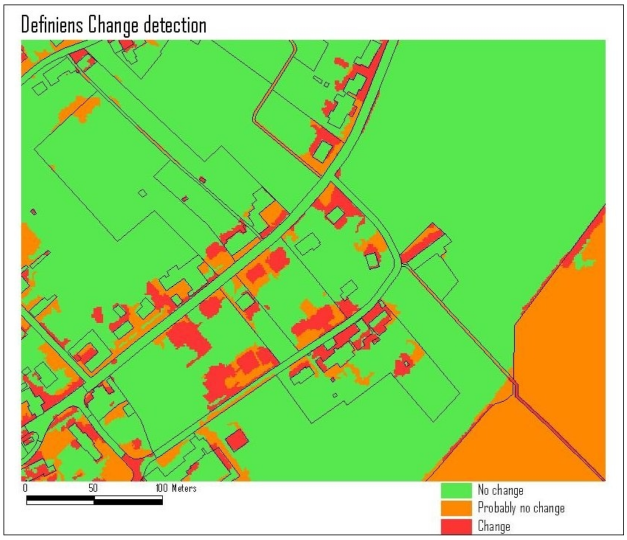


Figure 6: Evolution of the balanced accuracy for the four methods in case of mRMR

6. CHANGE DETECTION

Changes detection are looked for between the old database and a recent satellite image (Lillesand and Kieffer, 1994), by a post-classification comparison of the classification of images (Mas, 1999), possibly by using the old database as a priori knowledge, which assumes that the number of changes between the old database and the recent satellite image is low (Rellier *et* al. 2000; Walter, 2004).
A map between the old database updated and the results given by the Definiens classifier, based on Nearest Neighbor, has been established (cf. Fig. 7).

(a) Reference change detection: comparison DB0 and DB1 (change=red; no change=green)



(b) Definiens change detection: comparison DB0 and Definiens classification (change=red; probably no change=orange; no change=green)

Figure 7: Changes detection maps

To avoid the problem of occlusion and presence of bare soils in the crops depicted above, a third class « probably no change » has been created grouping segments with change from vegetation to bare soil from road to vegetation and from water to vegetation. This classification offers an over-estimation of change and is consistent with the idea that the no-change is more important in the point of view of a database producer who would like to restrict the areas where update is not necessary.
The figure 7 presents the reference change map obtained by comparison of the DB0 and DB1 and the change detection based on the Definiens classification. The new buildings are well detected but an over detection of the change is visible in the crops and in the gardens because of the bare soils and because of the building's shadows classified as built-up. The three classes of change detection allow to eliminate a part of this over detection by considering the « vegetation to bare soil change » as less probable than other changes.

7. DEMONSTRATOR

The different developed algorithms are integrated in a same software environment (cf. Fig. 9), based on existing open source libraries (OTB, GDAL, QT, R, Python…). This environment is divided into two layers:

- the *toolbox layer*, which consists in a coherent set of classes and methods using the features of the existing libraries and linking them together;
- the *application layer*, grouping different applications based on the toolbox layer with user-friendly graphic user interfaces (GUI).

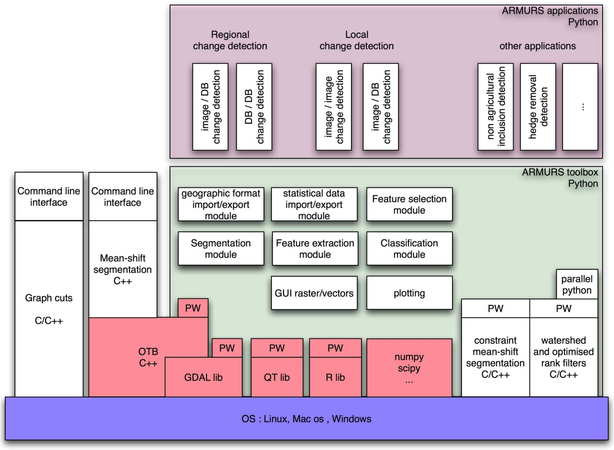


Figure 9: General organization of the demonstrator

8. CONCLUSIONS AND PERSPECTIVES

This paper has presented an approach to automatic change detection of man made structures in order to help database producers to update their topographical databases. Discussions with end users showed the crucial needs for automatic change localisation but also insisted on the importance of non changed areas.

In our dual scheme mixing a regional and a local approach, the regional change detection aims at finding changes at a coarse level from image and statistical data. Although indications could be derived individually from both subsystems, they are still to be fused to achieve the best performance. The local approach, solely based on VHR images, intends to detect changes between the old database and a recent image thanks to the classification of regions obtained by segmentation of this image. Among the different segmentation algorithms that we compared, the Mean-Shift delivered the best performance. In order to perform classification, each segmented region was described by a set of variables selected automatically by a learning procedure. The most discriminant variables appeared to be consistent with those found by visual interpretation. As far as the classification methods are concerned, the methods coming from R were found better than the ones from Definiens. Change detection obtained with Definiens still suffers from over-estimation. The change detection coming from the classical methods in R is still to be investigated.

All the developments are progressively integrated into a prototype which has been briefly outlined. It will turn to be a valuable tool to reduce the cycle of developments and test experiments on real data.

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10. ACKNOWLEDGEMENTS

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