Urban Indicator for Database Updating
A Decision Tool to Help Stakeholders and Map Producers

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Abstract: The issue of regular spatial databases updating is partly solved by the abundance of satellite images. It is, though, time consuming, requires qualified human resources, high financial costs and requests efficiency (Bernard, 2007). This article presents a semi-automatic tool for urban detection, to guide the stakeholders and the producers throughout the updating process. The industrial context of the study implies a fast, instantaneous applicative workflow, operational on various landscapes with different sensors; it is thus based on existing algorithms and software resources. The process is generic and adaptable, with a phase of uncorrelation, chaining a Minimum Noise Fraction transformation with a textural analysis, a learning phase, processed from an existing database, and an automatic modelling of the detected objects. The quantification of the results shows the successful recreation of the existing database (90% of its surface) with a 7% rate of potential big omissions. A specific highlight is made on the detection of disappeared buildings, corresponding to 17.5% of the potential important omissions. This process has run in "real" updating operations, on 1.5 and 6 meters resolution Spot6 images, a 15 meters Landsat-8 image and a 1.5 meters resolution Pleiades image. A quantification of its results is also proposed in this study.

1 INTRODUCTION

A tremendous amount of techniques in the change detection and database updating fields have already been explored. Lu et al., 2003 *"Change Detection Techniques",* give an overview of the most common techniques and qualify them in terms of characteristics, advantages, disadvantages and key factors. The heterogeneity of urban environments and the large number of mixed pixels inherent images often induced difficulty in urban land use/cover classification based on spectral signature (Lu and Weng, 2004). Recently, in the image change detection field, much attention shifted to advanced classification algorithms like neuronal network, object-oriented and knowledge-based classification approaches (Zhang and Wang, 2003). This study aims at updating an existing database of urban GIS objects with recent satellite imagery. The concept is that, having assumed that the number of wrongly detected GIS objects and the number of changes in the real world are substantially less than the number of all GIS objects of the data set, training areas can be derived from existing GIS data (V. Walter, 2000).

As this study is realised in an industrial context and aims at a generic and adaptable process, it is focused on a simple chain processing, based on existing algorithms. The easiest way to configure these algorithms is to use the ones implemented in software like ENVI and ArcGIS, available in the company. These tools are not mandatory as the image processing algorithms and statistical measures they use, are well-known by the community and can easily be reproduced in any computing languages. The choice of a radiometric analysis is made due to the simplicity of its implementation. The first phase chains a Minimum Noise Fraction transformation and a textural analysis resulting in two images: a relevant component from the MNF transformation and a grey scale image corresponding to the previous component's variance. The pixels' values in the two resulting images are combined with a selection of relevant objects in the database to establish a threshold. This learning phase finishes with the morphological reconstruction of the detected objects using a geodesic dilation with the existing database as a mask.

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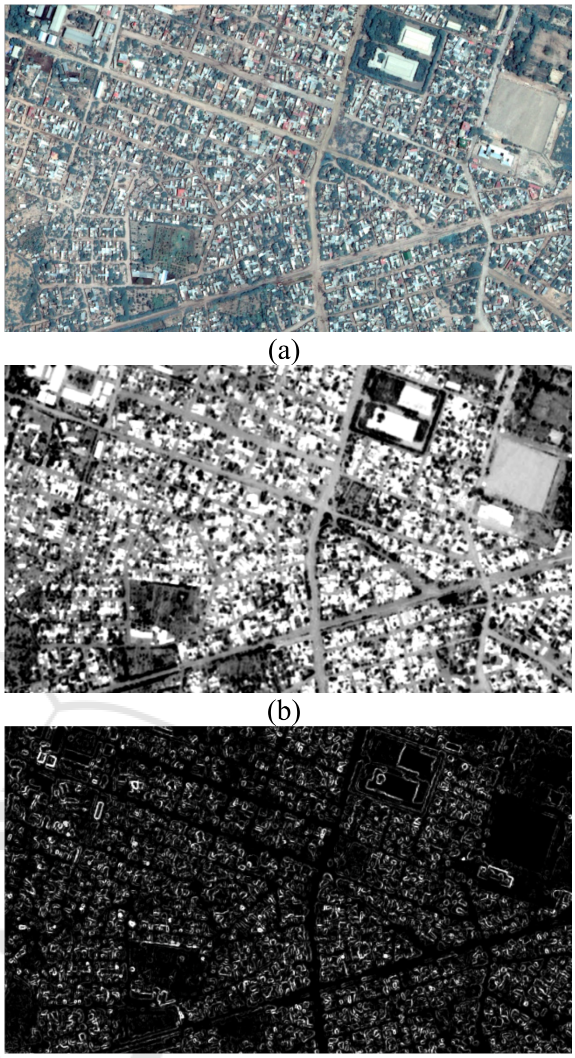
2 IMAGE PROCESSING

A multispectral Pleiades image (4 bands: blue, green, red and PIR) from 2015/09/02, with a 2 meters resolution, is processed. The method aims at extracting a specific thematic (urban objects) from spectral information within a complex landscape mixing vegetation, water, anthropogenic features, soil ... To reduce the dimensionality of the image and obtain a signal uncorrelated from the noise, a Minimum Noise Fraction forward transform is processed. The MNF transformation as modified from Green et al. (1988) and implemented in ENVI, is a linear transformation that consists of the following separate principal components analysis rotations (ENVI 4.2, 2005, Vermillion and Sader, 1999):

- The first rotation uses the principal components of the noise covariance matrix to un-correlate and rescale the noise in the data (a process known as noise whitening), resulting in transformed data in which the noise has unit variance and no band-to-band correlation.
- The second rotation uses the principal components derived from the original image data after they have been noise-whitened by the first rotation and rescaled by the noise standard deviation.

The result of the MNF first rotation is a two part data set, one part associated with large eigenvalues and coherent eigenimages, and a complementary part with near unity eigenvalues and noise dominated images. The information is compressed in different bands in which the redundancy of the information is eliminated. In our case, the majority of the information is contained in the first 3 bands.

Then, the analysis of the spatial variation of a component's grey scale levels is processed: the variance measures the dispersion of the values around the mean. The solution implemented in ENVI uses a co-occurrence matrix to calculate texture values. This matrix is a function of both the angular relationship and distance between two neighbouring pixels. It shows the number of occurrences of the relationship between a pixel and its specified neighbour. Haralick et al. 1973 refer to this as a "gray-tone spatial-dependence matrix". The texture analysis is done, in our case, on the second band of MNF components (Figure 1).



(a) (b) (c)

Figure 1: Image processing results: (a) Pleiades 2m image of Dire Dawa (Ethiopia), (b) MNF band 2, (c) Variance of MNF band 2.

The chosen MNF component (band 2) and the variance image are considered to be the resulting images of the image processing phase. The learning phase is applied on these two images.

3 LEARNING PROCESS

In order to calculate the threshold that will discriminate urban objects in the resulting images (Figure 1), the mean of the pixels' values that are located in areas labelled as "urban" amongst the available database, is calculated.

3.1 Labelling Objects as "Urban Areas"

The selection of anthropogenic objects in the database can be different regarding the type of the available database. The positive learning in an outdated database is justified by the rare disappearance of urban objects. In the case of this study, the buildings are represented individually so the selection of a sample can easily be done in the whole existing "building" layer. In other cases a simple SQL request can sort the data by attributes and randomly create fragments within the selection. The choice of urban areas results from a human consideration as it depends on the attributes the user considers as "urban". For example, urban places with a lot of vegetation should not be inventoried (like cemetery), nor punctual objects that are too thin to be representative of the local area (like pylon or water tanks). The choice of representative objects in the database is, then, flexible, and can be updated when changing area, if a new type of relevant anthropogenic object appears. Nevertheless, the list of these attributes has to be made just once for a data model.

3.2 Thresholding

In order to establish a threshold, the mean of the pixels' values located in fragments of buildings, is calculated on both images resulting from the image processing (Figure 2).

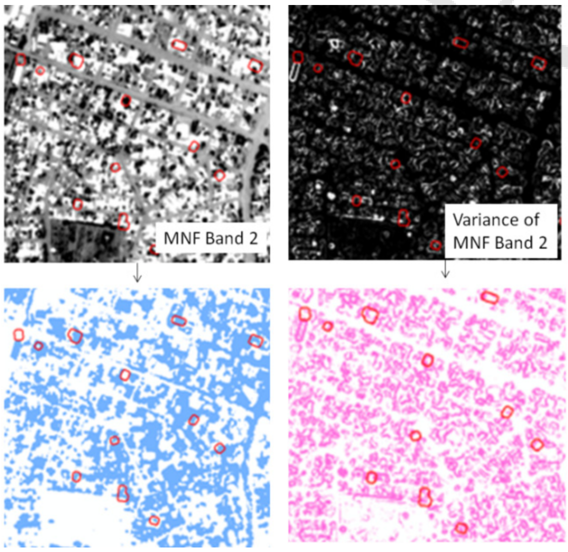


Figure 2: Thresholding results based on the fragments (red areas) in Dire Dawa, Ethiopia.

The final result consists in the intersection of the two thresholded images and is presented in Figure 3 over the original footprint of the buildings (grey polygons).

Figure 3: Urban detections in a Pleiades image (2m) over Dire Dawa (Ethiopia).

Figure 3 shows the multiple detections of anthropogenic objects inside the city and the differences with the database. These detections are still blobs with undetermined shapes, so for them to get the shape of the buildings, a step of reconstruction is necessary.

4 MORPHOLOGICAL RECONSTRUCTION

The geodesic dilation enables the reconstruction of the buildings' shapes. This is the dilation of an image constrained by another image (Figure 4). The first image is the assembly to dilate (marker) by a structuring element, which is a 3 pixels square (this is a size one dilation). The second image limits the expansion of the dilation: it is the mask.

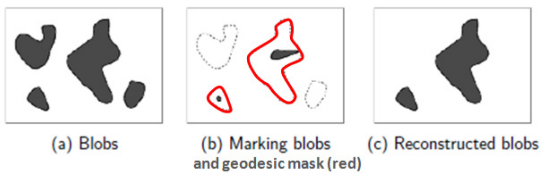


Figure 4: Blob extraction by marking and reconstruction, *Computer Vision (2015-2016),* Marc Van Droogenbroeck.

In the example of Figure 4, even if the marking blob only represents a small part of the mask it is, thus, reconstructed.

In this study, the anthropogenic detections are the blobs to reshape (red elements in Figure 5). Blobs intersecting the existing database are the markers to be dilated (blue elements in Figure 5), and the database itself is the mask (yellow polygons in Figure 5).

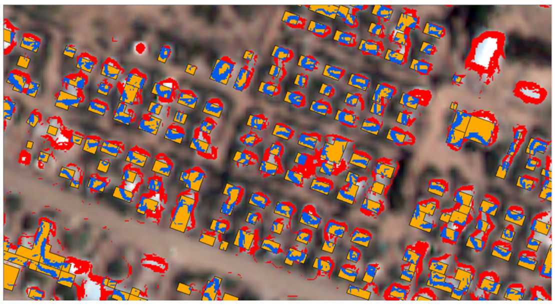


Figure 5: Geodesic dilation of the MNF detections.

This reconstruction allows obtaining maximum benefit from the MNF method, able to detect small and isolated buildings. A certain number of iterations lead to the reconstruction of the buildings existing in the database and detected by the MNF method (Figure 6).

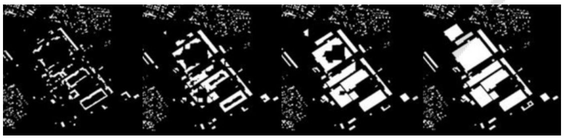


Figure 6: Evolution of the geodesic reconstruction (iteration from 1 to 185).

As the database used as a mask is outdated, detections corresponding to new buildings are out of the database: not all of the detections become markers. So, this morphological reconstruction must be completed by another step of reshaping. The anthropogenic detections that have not been reconstructed are reshaped.

5 AUTOMATIC RESHAPING

The automatic reshaping method is the one imbedded in the ArcGIS solution: Minimum Bounding Geometry.

The first step of the reshaping is the selection of the MNF detections that have not been reconstructed. This step is a simple GIS combination of merging and intersection that enables to analyse, for each MNF detection, if it is "well represented" by the reconstruction. If the detection is covered by the reconstruction polygon at a minimum of a 60 percent rate, it is, thus, considered as well represented in the reconstruction. If not, the part of the detection that is not covered at all by the reconstruction is isolated and reshaped, as shown in Figure 7.

(a)

(b)

Figure 7: Result of the reshaping (green polygons) from the MNF detections (red blobs) after the reconstruction step (yellow polygons).

Figure 7 illustrates the reshaping of a detection that is not correctly represented in the reconstruction step. Indeed, the blue circle shows an extended building visible on the image that is not in the existing database. The detection of this building is reshaped, as are the isolated surrounding ones. Notice that detections on the left side of the image are not reshaped because they are considered as "well represented" by the step of reconstruction (yellow polygons).

Polygons smaller than 5 m² are cleared from the results, considered as non significant.

6 RESULTS AND QUALIFICATION

The compilation of the 3 steps (MNF detection, morphological reconstruction and automatic reshaping) leads to a global detection of buildings whether they already exist in the database, or are new buildings (respectively yellow and green polygons in Figure 8).

Figure 8: Building detections in Dire Dawa

The process enables to delete buildings present in the database that do not exist anymore and to complete the database with new buildings whether they are simple extensions of buildings or obvious urban expansion (green polygons in Figure 8).

6.1 Quantification with Individual Buildings Composed Database

Out of the 58,473 buildings present in the database, 52,528 have been reconstructed which represent 89% of the original database (90% in surface).

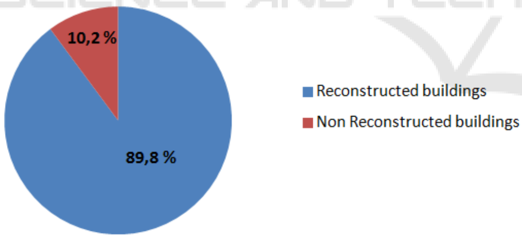


Figure 9: Result of morphological reconstruction.

Out of the 5,945 non reconstructed objects, 93 % of them are small buildings with a surface smaller than 100 m². In the 7 % of potential omissions of big buildings, the analysis of every and each building reveals (Figure 10) that nearly 75 % is a real omission, but in 17.5 % of the cases, the buildings that have not been reconstructed have actually been destroyed.

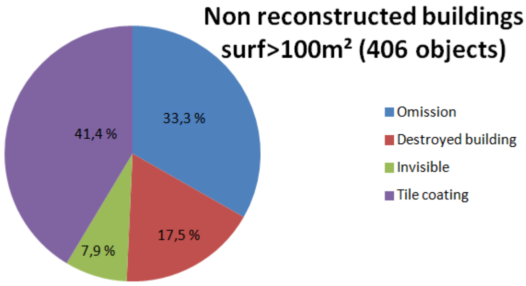


Figure 10: Analysis of the non reconstructed buildings which surface is over 100 m².

In terms of percentage, 11% of the initial database has been omitted (Table 1), but significant omissions only represent 0.23%.

Table 1: Error Type II considering the reconstructed objects.

	Total objects (reconstructed)	Total objects (in database)	Total omission (Error Type II)	Total omission (Error Type II) (%)	Important omission (buildings > 100m²) (Error Type II)	Important omission (buildings > 100m²) (Error Type II) (%)
Building reconstructed	52528	58473	5945	11	135	0,23

Figure 11 highlights buildings present in the database (red polygons) that are not reconstructed because they do not exist anymore in the recent satellite image.

Figure 11: Non reconstruction of destroyed buildings (red polygons).

Detecting destroyed buildings allows to rapidly point outdated objects to producers in the context of rapid mapping.

One can notice that a large amount of omissions is due to a tile coating of houses. Indeed, this type of coating has a similar signal to vegetation and is not representative of the majority of houses. The learning process, as it uses a sample of buildings, is based on the major type of coating which is not tile. This problem is inherent to a radiometry based analysis in a complex landscape. An optional improvement step can be performed using additional data (cf. 0 7 Improvement step).

An updated version of the database not being available, it is complicated to estimate type I errors concerning false positives. This would imply to check each of the reconstructed and reshaped polygons to validate their existence. This work has been done on a 100 polygons sample to estimate the quantity of false positives. Each polygon is checked and qualified as :

- positive: the corresponding building is clearly seen on the image. The shape of the polygon matches the reality or makes a relevant envelope around the buildings.

- false positive: no corresponding building on the image.

- not identifiable: the polygon does not really match the outline of the corresponding building. In this case it is possible that the building is not the detected element, but the detection is still relevant to point out anthropogenic features (cars and elements of the road are not comprised in these features).

The results are presented in Table 2.

Table 2: Error type I estimated on a sample polygons.

	Total objects	Positive	False positive (Error Type I)	Not identifiable	Mean size of false positive (m²)
Buildings reconstructed	100	72	5	23	30
Buildings reshaped	100	59	23	18	14
All buildings	100	65	8	27	17

This analysis is made separately on the polygons resulting from the phase of reconstruction and the ones resulting from the phase of reshaping, in order to estimate which one of the phases produces more errors. Table 2 highlights that the phase of reconstruction produces few errors of commission (5%). Moreover, the mean size or false positives in the reshaped buildings is around 30 m² which is a small surface. These results may be improved by changing the threshold of significant surfaces applied at the end of the reshaping phase (cf. 0).

6.2 Visual Qualification on Various Areas

The robustness of the MNF method has been tested with 3 different types of images (Spot6, Pleiades, Landsat), with 3 different spatial resolutions (1.5 m, 6 m, 15 m), with different landscapes (desert, dense urban area, mangrove, mine), on different swathes and with different levels of the database's obsolescence. Each one of the 11 tests were realized with the same settings: a unique list of representative urban objects for the learning phase (no "building" layer available, as in the Dire Dawa case), a variance calculated from the second band of the MNF result, and a size of fragment proportional to the pixel size. And each one of them led to an enriched analysis of the database's obsolescence. Most of all, the method has been tested in an operational context as an input data for the map producers.

In Saint-Louis (Senegal) the method spotted urban extensions, in Mali it detected a whole gold mine (Loulo) that was absent from the database (Figure 12). In the folowing figures the red marks correspond to the indicator and the grey areas correspond to the objects in the database.

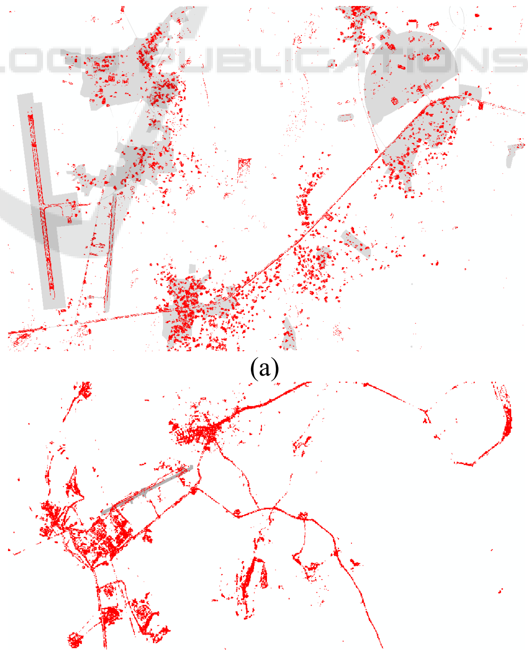
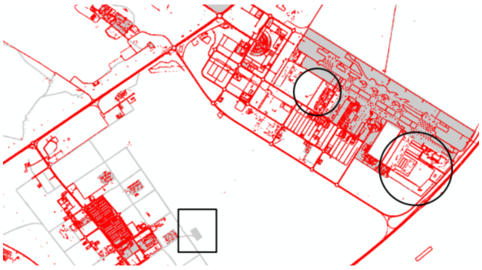
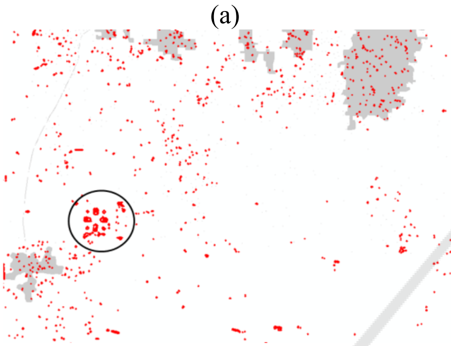


Figure 12: Urban extensions in Saint-Louis, Senegal (a) and detection of the Loulo gold mine in Mali (b).

At a different scale, in Dubai and Bamako new infrastructures and non-existing ones were highlighted by superimposing the indicator on the initial database (Figure 13).



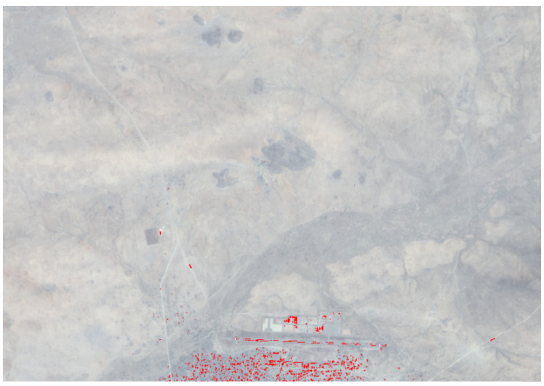
(a)



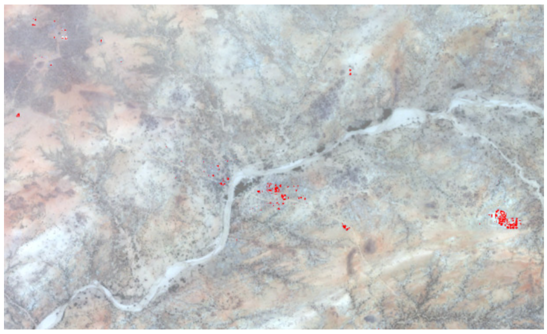
(b)

Figure 13: New (circles) and obsolete (square) infrastructures in Dubaï (a) and Bamako (b).

In addition of detecting the infrastructures, the process limits the false detections which are, in most of change detection methods, a limiting factor of use. In Lu and Weng (2006) the impervious surface was overestimated in the less-developed areas but was overestimated in the well developed areas. In our case, if the false detections still exist, they are so few that they don't perturb the visual analysis of the indicator. Figure 14 illustrates the ability of the process to concentrate the detections in the urban area amongst a wide desertic study area.



(a)



(b)

Figure 14: Desertic areas with very few false detections in Abeche (a) and Forchana (b), Chad.

Note that detections in (b) Figure 14 correspond to small settlements.

7 IMPROVEMENT STEP

If the method gives good results, an improvement is always possible. A choice of useful band is done after the MNF transformation. It appears that the urban information is not represented in just one band. The detailed process can be performed on another band or with additional data.

Surface elevation models provide a useful additional information as it is independent of the radiometric aspect of the data. With such a model, the tile coating of the buildings, in the Dire Dawa example, and the fact that its spectral signal is very close to vegetation, is not a problem anymore. The introduction of a geometric primitive (and not radiometric) allows a more invariant detection of buildings. Nevertheless, we chose not to work initially with a surface elevation model as we focused on the satellite image. Derivating such a model from a stereo or tri-stereo satellite image is thus possible, but is not the focusing point of our work. Champion, 2011 proposes an innovative database updating based on the improvement of a Digital Terrain Model (DTM) derived from a Digital Elevation Model (DEM).

In the case of Dire Dawa, DEM and DTM data were available. The vegetation index (NDVI) is calculated on the image to improve the distinction between elevated objects corresponding to buildings and other ones corresponding to trees. The elevation data, masked from the vegetation, is then used in the reconstruction step. In the first reconstruction step, 156 buildings with a surface superior to 200 m² were missing. The improvement step allows to reconstruct 73 % of the omissions and 70 % of the tile coating buildings (Figure 15).

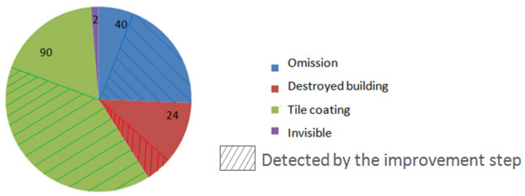


Figure 15: Improvement due to elevation and NDVI data.

The major inconvenient to this step is that it adds commission errors to the results. Indeed, Figure 15 shows the reconstruction of 33 % of destroyed buildings.

8 CONCLUSION

This semi-automatic tool provides detections of rapidly evolving features that does not match any evolution scheme: urban areas. It tends to answer the problem of efficiency in the updating databases process answering the questions "Where? How much? When?". The results can be presented in a map, to spot the necessity of the database update, it can be presented over the original image to help the producers to focus on important updating area (especially destroyed buildings), or it can be used at the end of the production process as a quality control. The method, using radiometric primitives improvable with geometric primitives, is adaptable to the type of landscapes, images, scales, and has been recognized as useful by independent producers during a real updating process test, not only as a detection of anthropogenic areas process, but as a real decision support instrument.

9 DISCUSSION

If this tool has proved its efficiency in a context of rapid mapping, it cannot be trusted as it is for an exhaustive automatic mapping. Indeed, a building that has changed its shape between the date of the database and the date of the image will probably be reconstructed as it was in the past.

If we were able to observe very few errors of commission (error type I) we didn't establish a real statistics on a representative amount of elements. Moreover, in the statistics established on type II errors, some missing polygons were considered as omission but the field reality (the image) was obviously different than the representing database: in this case the qualification of omission is not really correct.

In this study, two types of databases were tested. The most advanced case (Dire Dawa) used a database in which the buildings were individually drawn. This allowed us doing the reconstruction and the derived statistics and declaring the method efficient. This is not possible with a database in which the buildings are not individually drawn. This is why a simple visual qualification is done on the other tested areas (§ 6.2). When using this type of database another type of statistics can be calculated to estimate the changes and the amount of work in the pre-production phase, but the quality assessment of the method by calculating the reconstruction rate is not possible. Another option would be to compare our detection to other urban products (mixing different types of data) like Global Urban Footprint or Landscan.

REFERENCES

ArcGIS for desktop Help *http://desktop.arcgis.com/en/arcmap/latest/tools/data-management-toolbox/minimum-bounding-geometry.htm*

M. Bernard, T. Rousselin, N. Saporiti and M. Chikri, 2007 *"Data harmonisation and optimisation for development of multi-scale vector databases"*, ISPRS Workshop on Updating Geo-Spatial Databases with Imagery, Urumqi.

N. Champion, 2011 *"Détection de changement 2D à partir d'imagerie satellitaire. Application à la mise à jour des bases de données géographiques "*, thesis

ENVI 4.2, 2005 User's Guide Volume 2 Chapter 7.

A.A. Green, M. Berman, P. Switzer, and M.D. Craig, 1988 "*A transformation for ordering multispectral data in terms of image quality with implications for noise removal*". IEEE Transactions on Geoscience and Remote Sensing (GRS), Volume 26 No 1 p.65-74.

R. Haralick, K. Shanmugan and I. Dinstein, 1973 *"Textural features for image classification"*, IEEE Transactions on systems, man and cybernetics Vol. SMC-3, N°6, pp.610-621

D. Lu et al., 2003 *"Change Detection Techniques"*, International Journal of Remote Sensing vol.25, no 12, 2365-2407.

D. Lu and Q. Weng, 2004 "*Spectral mixture analysis of the urban landscapes in Indianapolis with Landsat ETM+ imagery"*, Photogrammetric Engineering and Remote Sensing, 69, 973-980.

D. Lu and Q. Weng, 2006 "*Use of impervious surface in urban land-use classification"*, Remote Sensing of Environment 102 (1), 146-160

M. Van Droogenbroeck, 2015-2016, *"Computer vision"*, open Repository and Bibliography, Université de Liège.

S. Vermillion and S. Sader, 1999, *Use of the Minimum Noise Fraction (MNF) Transform to Analyze Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) Data* *of Northern Forest Types,* AVIRIS workshop bibliography

V. Walter, 2000 *"Automatic change detection in GIS databases based on classification of multispectral-data", ISPRS Archive Vol. XXXIII Part B4, Amsterdam.*

Q. Zhang and J. Wang , 2003 *"A rule-based urban land use inferring method for fine-resolution multispectral imagery",* Canadian Journal of Remote Sensing, 29, 1-13