Object-Based Approach and Tree-Based Ensemble Classifications for Mapping Building Changes

Loubna Elmansouri
Geomatic unity, SURFACES Laboratory
Liege, Belgium
l.elmansouri@student.ulg.ac.be
Hassan II Institute, Department of Topography
Rabat, Morocco
l.elmansouri@iav.ac.ma

***Abstract*-- The aim of this paper is to efficiently detect and identify the building changes from newly registered very high spatial resolution (VHSR) image by comparing with outdated map. The whole process is performed mainly on four steps. First, the image was segmented to generate primitives, which are then represented by a feature vector composed from spectral, geometric, textural and contextual attributes. Thereafter, tree-based ensemble methods (Bagging, Random Forest and Extremely Randomized Trees) are used in a classification step. The final objects' prediction is deducted with respect to the better classifier error rate. Last, a post classification change detection step allows to identify the segments which represent building changes. The data used in this research concerns the city of Rabat (Morocco). A Quickbird image has been used with an old map at the scale of 1:10,000. Regardless of the quality of the detected buildings' shape, the method achieves good rates of completeness and correctness.**

Keywords; Building changes detection; (VHSR) image; Decision Trees; Random Forest; Extra Trees.

I. Introduction

Updated topographic maps are essential in many applications such as land and urban planning. Their update consists on visual interpretation of orthophotos which is time consuming and expert dependent. Recently, some academic studies and cartographic agency experiments present the update process as two automatic steps: (1) change detection and (2) map revision [1,2,3,4]. The first step is the most difficult [4,5]. It can be performed by comparing recent extracted data from a VHSR image with the map to be updated. An object-based approach is more suitable for detecting change. Each extracted polygon is analyzed as a whole allowing more interpretations of change nature. It's almost free data dependent, which ensures its transferability and let it appear as a potential framework for a standard solution of automatic change detection [5]. A typical object-based change detection process relies on two separate stages: (1) persegments-image classification and (2) post classification image-map comparison. First, the image is segmented into groups of spatially connected pixels with respect to some homogeneity criterion [6]. Resulting clumps as the unit of the rest of the process, are more intelligent than individual pixels. They could be described by other features than spectral ones(e.g. geometric and textural) and release better their contextual relationships[1].

Classical classifier cannot handle the high number of features in object-based analysis that's why advanced supervised learning classifiers are becoming more used in VHSR image classification [6]. These include, but are not limited to, decision tree (DT) and tree-based ensemble methods. They are a good data reduction tool and are able to detect multivariate interacting effects between features. They are also non-parametric. No assumption on the distribution of the data is required, it is thus easy to adapt for new datasets. In DT algorithm, a learning set is successively split into binary homogenous subsets based on "if-then" rule tested at each internal node of the tree. The terminal node will be labeled by the majority class. At the end, the tree results in a number of class prediction rules that are used to create a predictive model. Classification accuracy from DT algorithm is often greater compared to using maximum likelihood or linear discriminate function [7]. In change detection context, DT have been used, for example, by Matikainen et al. [8] for mapping urban building changes, by Ruiz et al. [1] to create and to update a high scale database and by Chubey et al. [9] for forest inventories.

The original classification single trees can overfit the training data. It's very much improved by ensemble methods. The tree-based ensemble methods rely on randomization to generate a more stable prediction. These methods are Bagging, Random Forests (RF) and Extra-Trees [10]. Bagging (for “Bootstrap AGGregatING”), builds multiple training subsets by random replacement from the primary learning set. Each subset is inducted as the classical DT algorithm explained above. The Bagging aggregates the predictions of all developed trees by a majority vote to produce the final class. RF combines Bagging with only a random selected subset of k input attributes at each test node. In the Extra-Trees (for “EXTremely RAndomized Trees”) method, each tree is build from the complete learning set but at each test node, the best split is determined by randomly selecting one attribute. A complete review can be found in

[10,11]. Another advantage of these algorithms is their internal faculty to partition learning set into separate sets for training and validation. This allows to automatically determine all their own parameters through cross-validation. Further details about these algorithms will be given thereafter.

Our main objective in this paper is to present a complete automatic procedure for detecting changes. We limit the problem to map building changes which is the most dynamic class in urban and suburban mapping. The proposed methodology is based on a post classification image-map comparison. Tree-based ensemble methods are used in conjunction with an object-based image analysis.

The article is organized as follows: in section 2, study area, data and preprocessing are described. The whole methodology is detailed in section 3. Section 4 provides a discussion of the experimental results that validate the proposed method. Finally, some conclusions are drawn in section 5.

II. STUDY AREA, DATA AND PREPROCESSING

A. Study area and Data

The test area is located in Rabat (Morocco) which is a flat relief city. It shows a new arranged residential district which is divided on a regular frame. It's composed of single-family dwellings. Buildings are characterized by different size, shape and construction material.

Our approach was tested on a 1:10.000 scale map and a Quick Bird image. The map has been produced in 1999 from aerial photographs restitution by the National Cartographic Agency of Morocco. The satellite imagery was acquired on August 2004 and has a resolution of 0.61 m in panchromatic band and 2.4 m in the four multispectral ones. Considerable changes have been occurred between the two dates.

B. Preprocessing

The data pre-processing consists of two major steps: (1) Pan-sharpening multispectral bands by the panchromatic band. The four bands obtained have a higher spatial resolution than the multispectral image and they well preserve the spectral properties from the multispectral image. They will be used in feature extraction stage and (2) as our change detection approach is based on an image–map comparison, precise co-registration between the two data is crucial. Any miss registration can lead to false alarms in detecting change. A polynomial of first order was used; the obtained Root Mean Square Error (RMS) is 0.72m.

III. METHODOLOGY

The proposed change detection methodology consists in a post classification comparison between a VHSR image and an outdated map. The principal contribution of our methodology is that it integrates advanced image classification within an object-based analysis. Extracted objects are characterized by different attributes (spectral, geometric, textural and contextual). Objects in the map are used to train and to tune parameters in classification learning step. The flowchart of the whole methodology is represented in figure 1. All steps are explained thereafter.

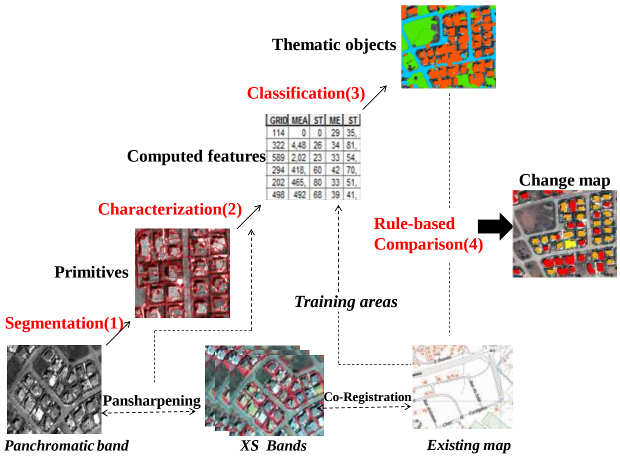

Figure 1. Flowchart of the proposed methodology.

A. Image segmentation

In this work, a variant of the Watershed Transform (WT) [12] was developed to segment the panchromatic band. The WT holds its foundations from the mathematical morphology. The idea is to consider the image as a topographic surface where the intensity of pixel is considered as a height. Points with divergent flow direction are then seen as crests (objects' contours) which separate catchment basins (homogeneous regions) created from local minima of image (pour points). Usually the WT is calculated from the gradient direction. In this article, the study area concerns the urban context, where the most objects are with almost regular shape, e.g. roads and buildings. That's why a distance map computed from the catchments contours is used to support the WT calculation.

In its original version, the WT produces a profuse number of regions. The small ones come from no-significant local variations of the intensity (false minima). This problem is more marked with the noisy VHSR image. To avoid this over-segmentation, the real minima are to be imposed. All minima in distance map whose depth is less than a fixed threshold are suppressed. We select the threshold automatically according to dynamic range of the distance map.

B. Features Extraction

Primitives resulting from segmentation were characterized by 4 categories of zonal statistics. Spectral attributes are statistically derived (mean and standard deviation) from 8 spectral and ancillary channels including 4 pansharpened bands and 4 spectral indices (NDVI (Normalized Difference Vegetation Index), SBI (Soil Brightness Index), BAI (Built-Up Areas Index) and SI

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(Shadow Index)) [4]. Geometric features like area, Elongation index and Compactness index were computed. Nine texture features are extracted from the GLCM (Grey Level Co-occurrence Matrix) calculated for all pixels of a primitive, instead of for a regular window size [13]. In our methodology we propose also to take into account the location of the primitive. That's why for each primitive, the all described attributes of its 4 important neighboring primitives were taken as its contextual attributes. In total, 148 features were generated for each primitive.

C. Object-based classification

The classification consists in finding the thematic class of a primitive. After analyzing objects on existing map and available images, we identified 5 classes: buildings, roads, low vegetated areas, urban vegetation and shadow. Objects in the existing map are organized in three themes, buildings, roads and vegetation. The third layer includes urban vegetation (mixels tree-lawn) and low vegetated areas. In our change detection purpose we look for the large low vegetated areas that could have changed to build up areas. However, no information concerning vegetation type is associated to exiting vegetation objects. Whereas such knowledge is necessary to use map objects as training data. Nevertheless this information can be obtained from image data. On the other hand, shadow segments could not be trained from existing map. In order to cope with this, the classification is performed in a two pass scheme: (1) urban vegetation and shadow discrimination and (2) Tree-based ensemble classifications.

First the mean value of the NDVI layer was used to create a binary mask. Two classes were defined, urban vegetation and non-urban vegetation. The latter class was further subdivided into shadow and non-shadow classes. This separation is done by thresholding the SI layer. Shadow segments are the darker in the image, so it's assumed that they have the lower SI value. The non-shadowed primitives are then classified in 3 themes: buildings, roads and low vegetated areas thanks to tree-based ensembles methods. The training samples are automatically selected from the old map. For every object of each layer in the old map, the segment that corresponds spatially to it is identified on the segmented image. The primitive is a priori retained for training if its geometric properties (shape and area) are close from those of the map object. Specific class rules could be added at selection stage. For example, having a large area is an additional criterion for selecting segments to train low vegetated class. Resulting segments attributes data were used as a learning set to generate tree-based ensemble models.

We have decided to employ tree-based ensemble methods for classification for many reasons.

(1) They produce multiple models which will feign the variability of real data.

(2) They have been successfully applied in a variety of pattern recognition and they are often unexcelled in accuracy among current supervised learning algorithm (e.g. Support Vector Machine [7]).

(3) They have been used increasingly in recent years in VHSR image classification and with better results than other classification approaches [14]. For example, for determining agriculture management practices [14], as well as for land use/land cover mapping change projects [15].

Many statistical packages Pepito [16], R, S-Plus [14], CART [6] and Matlab [17] propose a complete toolbox for implementing Bagging and RF. The developed codes in [11] include also the Extra trees algorithm; they were used to implement our classifications. Two parameters are to fix, splitting criterion and stop splitting criterion. To split a node, a score measure is defined by minimizing the impurity of the output variable in the local subset (which also could be expressed by maximizing the class separation at each node). The GINI's index [11] is used. For the second criterion, It's commonly used that de development of a branch stops when the number of instance is lower than a given threshold or when impurity cannot be further reduced (when the output variable is constant). With the exception of k the number of a randomly selected attributes in RF which is fixed at the root square of the total number of attributes, all other parameters (number of developed trees(T) and stop splitting criterion (Nmin)) were adjusting by cross validation from learning set according to the best error rate.

D. Rules-based change detection

Changes detection are looked for by a post-classification comparison of the existing building layer with the building classification results, which is converted without generalization to a vector format. For comparison, each polygon must be matched with its counterpart in the other dataset. The obtained positional accuracy of the map and image is so good that matching of polygons can be based on their overlap. However, when defining rules for detection change, thresholds must be large enough to tolerate small errors in location and shape of buildings. These errors result mainly from (1) attributes errors propagation and (2) intrinsic difference in the nature of objects in both datasets (map and image). According to the ratio of overlap area (A_overlap) between a pair of buildings on the map(A_map) and in the building detection (A_detection) result, the correspondence between polygons is performed. We have defined 5 classes for buildings change:

New building: no building on the map corresponds to the detected building with:

$$A\_overlap \,/\, A\_detection < Thr1 \qquad (1)$$

Demolished building: no building on the building detection corresponds to the building in the map with:

A_overlap / A_map< Thr1 (2)

Confirmed existing building: building on the map corresponds to one in the building detection with:

A_overlap / A_map > Thr2 (3)
and
A_overlap / A_detection > Thr2 (4)

Enlarged building: building on the map corresponds to one in the building detection with:

A_overlap / A_map > Thr2 (5)
and
A_overlap / A_detection < Thr2 (6)

Re-examination needed: includes all other cases where none of the aforesaid conditions is verified.

In our case, Thr1 is fixed to 10% in order to take into account the accumulated errors throughout the change detection process. For the second threshold Thr2, Rutzinger et al. [18] suggested that a threshold value between 50% and 70% should be selected for this type of comparison. In [19], the authors propose to select the threshold of 80% for industrial areas, 70% for the apartment house areas and 60% for areas with smaller detached houses. We select Thr2= 60% because our first purpose is to detect all unregistered buildings without caring too much about the quality of their shape.

IV. EXPERIMENT RESULTS, EVALUATION AND DISCUSSIONS

A. Classification

First of all, aforesaid classification algorithms were evaluated. In an object-based classification method, the unit for classification is the object. Consequently, the sampling unit for validation also has to be an object. 99 segments selected by a random stratified sampling from the no learning data and annotated visually from the image by an independent interpreter were used as validation data. The overall accuracy, the coefficient kappa and its standard deviation were calculated [20]. Table I presents the best result obtained for each classifier.

TABLE I. CLASSIFICATION ACCURACY FOR ALL EXPERIMENTED CLASSIFICATION ALGORITHMS.

Algorithm	**Overall accuracy %**	**Kappa %**	**σ_{Kappa}**
Classical DT	59.18	0.50	1.1
Bagging (T=50)	73.56	0.64	0.11
RF (T=200)	82.05	0.72	0.04
Extra Trees((T=500)	82.8	0.73	0.02

As expected, the results from classical DT are not good what is due to the high variance of this method, moreover that no pruning technique was used. Note that the three scores of tree-based ensembles methods are better than the classical DT (14% at list). RF and Extra trees present better scores than Bagging with a light superiority of the Extra trees. The RF incorporates a features selection process that's why it maintains an increase even if with a high number of attributes. Extra trees builds completely random independent trees, the constructed model lacks sensitivity to noise and is not subject to overfitting, which explain the stability of its results ($\sigma_{Kappa=}$0.02).

For the rest of the process, the predictions from Extra trees will be adopted. Table II shows the error matrix. A good separation between "roads" and "buildings" is achieved. The major problem in the classification result is the asymmetric confusion between "buildings" and "low vegetated" segments, which is the origin of the small kappa's value. Adjacent segments to the buildings are mixture of grass, trees and asphalted surfaces; they are either court yards or terraces. The classification algorithm labels them as buildings because of their close spectral response to building. Moreover on the one hand, their area is small and on the other hand, the image acquisition date (August) is not suitable for separating low vegetated and build-up areas in Morocco. The classification result is shown in figure 2.

TABLE II.EXTRA TREES CLASSIFICATION CONFUSION MATRIX (B: BUILDING, R: ROAD, LV: LOW VEGETATED).

		Reference								
		B	**R**	**LV**	**Total line**	**Producer's%**	**Omission %**	**Overall %**	**Error rate %**	**Kappa**
Classification	**B**	44	1	0	45	97,8	2,2	82,8	17,2	0,73
	R	3	21	0	24	87,5	12,5			
	LV	12	1	17	30	56,7	43,3			
	Total Column	59	23	17	99	80,6				
	User's %	74,6	91,3	100	88,6					
	Commission %	25,4	8,7	0						

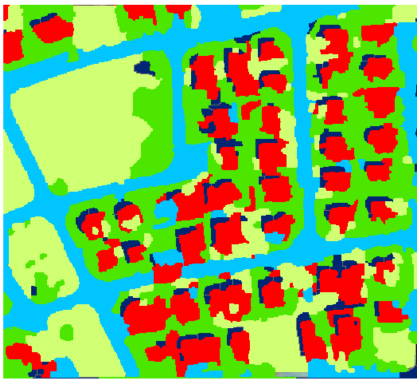

Figure 2. Classification result (building road low vegetated shadow urban vegetation).

B. Change detection

Applying change detection rules directly to the buildings class leads to an overestimation in changes. A series of contextual rules were then defined so as to optimize the building classification result. They are based on the fact that the building cast shadow in the opposite direction of the sun. First, for each shadow segment, its neighboring segments in building class with the closest azimuth to the sun's were selected. Once confirmed as a construction segments, an homogeneity analysis is then performed to detect the construction segments from their neighboring segments among the remaining ones in the building class. We run this last step iteratively until no neighboring is detected yet. Segments which are not selected at any iteration were excluded from the further process.

To evaluate change detection results, a reference change map was performed by an exhaustive computer assisted image interpretation using the image and the old map as backdrops. Buildings in the same class in reference change map that touch each other in space were considered as one building. The concept and parameters of the change detection validation scheme were similar to the ones defined for the change detection stage. If there's any overlap higher than 60% between buildings of a pair on our change detection result and in the reference change map and which are labeled by the same class in both datasets, this is considered as a good detection. However, when the two counterpart objects are labeled separately, the detection is correct but with a wrong identification of change nature. Both automatic change detection result and reference change map are presented in figure 3, the confusion matrix of the change detection validation is given in table III.

(a)

(b)

(c)

Figure 3. (a) Building layer in 1999,(b) Our change detection map, (c) Reference change map (New B. Confirmed Existing B. Enlarged B. Re-examination needed).

TABLE III. CHANGE DETECTION CONFUSION MATRIX

		Reference				
		N B.	C B.	E B.	D B.	Total
Change detection	New B.	23	0	0	0	23
	Confirmed Existing B.	0	22	0	0	22
	Enlarged B.	0	01	0	0	01
	Demolished B.	0	01	0	0	01
	Re-examination needed	0	02	0	0	02
	Total	23	26	0	0	49

The comparison of the change detection result of our automatic procedure with the reference change map shows that 46 buildings from the 49 ones present on the area are detected so as 94% for completeness rate. The change nature for 45 buildings of the detected ones is correctly identified so as 92% of correctness rate. Only one detected building has a wrong class of change. It concerns an unchanged existing building which is labeled as enlarged one by our approach. This is due to the segmentation step, as we merge small segments with their adjacent ones to overcome the over-segmentation problem, some segments become larger. Omission error is 2%, only one building is completely not detected (demolished). It was classified as a road segment. This miss-classification is explained by the selected stopping criterion (Nmin=1) which forced the branch to continue split until only one segment per class. Two existing buildings were detected with smaller surface area than in nature, which doesn't allow verifying the conditions to be confirmed as existing buildings. Indeed, the missing parts were first classified as buildings, but as they are composed of mixed pixels (build-up areas and vegetation) they present a spectral heterogeneity with their neighboring which leads to their elimination by homogeneity post classification rules. Further attention is needed to this change detection class. Note that no false alarm was indicated.

To have geometric information about detected changes, an area ratio was calculated for each

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detected building. It presents the object surface area in reference map which is covered by the object at the change detection result of our automatic approach. The mean ratio of detected area per building is 85%. More geometric evaluation is planned in the further developments.

V. CONCLUSION AND FURTHER DEVELOPMENT

An automatic change detection process was proposed to map building changes. The first obtained results (94% for completeness and 92% for correctness) are promising and are comparable to the best results for similar researches found in literature (98% for completeness and 96% for correctness) [5]. The whole process is conceived in four separate stages. The basic concepts for each stage are chosen to be opened and generic. So that the minimum of adaptations will be required when the process is applied in a different context.

Completeness is a decisive indicator since it is important to be exhaustive, to be sure not to miss any changes. Searching for undetected changes is more difficult and contrary to the basic goal of using automated change detection. For new buildings class, it's completely correctly detected which might lead to an operational use of our procedure. The result of this class could be used to trigger and to guide on-site inspections by the control authority. Unchanged existing buildings class represents 53% of the total number of buildings in the test area. This class is correctly detected with 85% rate. In theory, when updating the map, operator could bypass this class and concentrate on checking the changed ones. Much time and costs might be saved.

Up to now, our main goal was to develop a complete automatic procedure for mapping buildings changes. Once ready, additional studies are underway to show if the procedure is transferable for other contexts. Different datasets with heterogeneous areas are planned to be tested. Practical tests are also needed to show if the results are geometrically accurate enough for an operational use.

To update the old map, the changed buildings must integrate it. A shape adjustment step appears necessary to correct their contours before. Developing snakes from the detected building contours to create corrected ones seems to be attractive.

REFERENCES

[1] L.A. Ruiz and T. Hermozilla,"A multi approach and object-based stratey for updating lu/lc geo-databases based on Worldview-2 imagery", 2011.

[2] V. Walter, "Object-based classification of remote sensing data for change detection". ISPRS Journal of Photogrammetry & Remote Sens., 2004, pp. 225-238.

[3] D.A. Holland, D.S. Boyd and P. Marshall," Updating topographic mapping in Great Britain using imagery from high-resolution satellite sensors". ISPRS Journal of Photogrammetry and Remote Sensing 60 (3), 2006, pp. 212-223.

[4] M. Bouziani, K. Goïta and D.C. He, "Change detection of buildings in urban environment from high spatial resolution satellite images using existing cartographic data and prior knowledge". In: Proc. IEEE International Geoscience and Remote Sensing Symposium, Barcelona, July 2010, pp. 2581-2584.

[5] N. Champion, "Detection of Unregistered 2D DataBases". European Spatial Data Research report, 2010.

[6] R.L. Lawrence and A. Wright, "Rule-based classification systems using classification and regression trees (CART) analysis", Photogrammetric Engineering & Remote Sen., 2001, pp. 1137-1142.

[7] M.A. Friedl and C.E. Brodley, “Decision tree classification of land cover from remotely sensed data”, Remote Sens. Environ, 61,1997, pp. 399-409.

[8] L. Matikainen, J. Hyyppä, E. Ahokas, L. Markelin and H. Kaartinen, "Automatic Detection of Buildings and Changes in Buildings for Updating of Maps", Remote Sens. 2010, pp. 1217-1248.

[9] M.S. Chubey, s.e. Franklin and M.A Wulder, "Object-based analysis of IKONOS-2 imageryfor extraction of forest inventory parameters". Photogrammetric Engineering and Remote Sensing, 2006,72, pp. 383-394.

[10] R. Maree, "Decision trees for automatic images classification". Phd Thesese. Ulg university, 2005.

[11] P. Geurts, A. Irrthum and L. Wehenkel, "Supervised learning with decision tree-based methods in computational and systems biology". Mol Biosyst 5, 2009, pp. 1593–605.

[12] B.T.M. Jos and A. Meijster," The Watershed Transform: Definitions, Algorithms and Parallelization Strategies". Fundamenta Informaticae. 2001.

[13] R. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification". IEEE Transactions on Systems, Man and Cybernetics, 3(1),1973, pp.610-621.

[14] J. D. Watts and R. L. Lawrence, "Merging Random Forest classification with an object-oriented approach for analysis of Agricultural Aands". ISPRS Journal of Photogrammetry and Remote Sensing, Working Group VII/4.2010.

[15] C. Leignel, O. Caelen and O. Debeir, "Detecting man-made structure changes to assist geographic data producers in planning their update strategy". ISPRS Journal of Photogrammetry and Remote Sensing, 2010, part,4-8-2-w9.

[16] www.pepite.be

[17] Matlab (2010). Matlab documentation: Image processingtoolbox. http://www.mathworks.com/help/toolbox/images)

[18] M. Rutzinger, F. Rottensteiner, N. Pfeifer, "A comparison of evaluation techniques for building extraction from airborne laser scanning". IEEE J. Selected Topics Appl. Earth Obs. Remote Sens. 2009, 2, pp,11-20.

[19] L. Matikainen, L. Hyyppä and H. Kaartinen, "Automatic detection of changes from laser scanner and aerial image data for updating building maps. Remote Sensing". The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2004,XXXV/B2, pp.434-439.

[20] R.G. Congalton, "Accuracy assessment of remotely sensed data: future needs and directions". In: Proceedings of Pecora 12 land information from space-based systems. 1994, pp. 383- 388.