AUTOMATIC CHANGE DETECTION IN URBAN AREAS UNDER A SCALE-SPACE, OBJECT-ORIENTED CLASSIFICATION FRAMEWORK

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ABSTRACT:

In this paper an object-based classification framework is introduced for the automated monitoring of changes in urban areas. Morphological scale space filtering is embedded in the processing procedure constraining qualitatively the multi-level segmentation and thus, the structure of object hierarchy. The elegantly simplified images provide a more compact and reliable source in order to generate image objects in various scales. Multivariate alteration detection (MAD) transformation is applied on the simplified images towards the identification of changes. Experimental results indicated that important information, regarding the changes of man-made features, is concentrated to the higher order MAD components. While, the first component has, in most cases, maximum variance and ideally carries the maximum amount of information on changes, the second one has maximum spread in its intensities subject to the condition that it is statistically uncorrelated with the first one, and so on. While the man-made changes are unrelated with the changes of phenological cycle and image noise, it is quite common that such changes are highlighted in higher order components. Last but not least, the labeling of the most significant changes is addressed through an effective object-based set of rules over the MAD components. The quantitative and qualitative evaluation of the developed scale-space, object-oriented classification framework indicates the potentials of the developed approach.

1. INTRODUCTION

The integrated analysis of multi-temporal remote sensing data and the automatic and accurate recognition of changes in urban environment are crucial components towards the efficient updating of geographic information systems (GIS), government decision-making, urban land management and planning. Although urban land cover changes can be monitored by traditional ground survey procedures, nowadays high resolution satellite remote sensing sensors provide a cost-effective source of information for detecting important spatial patterns of land cover change over a large geographic area in a recurrent way. In particular, recently many research efforts, have introduced advanced proceeding methods for monitoring the dynamic urban environment from remotely sensed data.

The variety of change detection techniques has been researched extensively from a theoretical and practical aspect during the last decades. Lu et al. (2004) studied the most popular pre- and post- classification methods for various applications and they grouped them into seven types of change detection methods: algebra, transformation, classification, advanced models, Geographical Information System (GIS) approaches, visual analysis and some other approaches. Sui et al. (2008) also reviewed and categorized the change detection techniques in seven categories: namely, direct comparison, classification, object-oriented methods, model method, time series analysis, visual analysis and the hybrid method. Despite the differences regarding the categorization approach (Li et al., 2003; Radke et al., 2005), it has been generally agreed that there isn't any specific single methodology that is appropriate for all the case studies (Sui et al., 2008).

Nowadays, the main interest is concentrated on the development of automated approaches for the precise identification of urban land cover changes by analyzing multi- spectral/temporal data. Digitizing manually land cover changes and traditional ground survey procedures on the one hand may result to an accurate product but on the other hand, are very time-consuming and inappropriate to record the rapid alterations of urban areas (Champion et al., 2009b). To this end, the automation of change detection process for the efficient updating of geospatial databases has gained significant attention lately (Holland et al., 2008; Bouziani et al., 2010).

However, automatic identification of urban alterations remains a difficult task, despite the sub metric spatial resolution of the latest satellite images. The different light, atmospheric and soil moisture conditions at the two dates of imagery acquisition (Jensen, 2005), the complexity of urban environment and the spectral, shape and size variation of man-made objects hinder the automatic detection of changes (Donnay et al., 2001). The aforementioned variables limit the effectiveness of traditional change detection approaches -like image algebra, image transformation techniques or post-classification analysis- and thus, require new, more sophisticated ones (Holland et al., 2008). In certain case studies ancillary data like any existing geodatabase (Bouziani et al., 2010) and LIDAR data (Champion et al., 2009b) have been employed towards an integrated change detection system. In general, advanced methods is much likely to be model-based approaches and take into consideration the available intrinsic information of the objects such as colour, texture, shape and size, and topological information as location and neighbourhood (Blaschke, 2004; Champion et al., 2009a).

To this end, in this paper an object-based classification framework is introduced for the automated monitoring of changes in urban areas from multi-temporal imagery data. Scale-space filtering images facilitated the process, since the elegantly simplified images provided a more compact and reliable source in order to generate image objects in various scales. The Multivariate Alteration Detection (MAD) algorithm was applied on the images for the detection of changes and a knowledge-based classification scheme was introduced for the labelling of the changes of interest. In order to simplify the change detection problem, only the buildings were selected as objects of interest in this change detection study.

The rest of this paper is organized in the following way. In Section 2 the proposed change detection methodology through scale-space filtering is described. Experimental results and their analysis are described in Section 3. The performed quantitative and qualitative evaluation of the developed methodology is presented in Section 4. Sections 5 and 6 are dedicated to discuss the methodology and the results, conclusions and feature work.

2. METHODOLOGY

The developed change detection methodology is based on advanced image processing techniques like nonlinear scale space filtering, multivariate alteration detection algorithms and certain knowledge-based classification schemes.

2.1 Morphological scale space filtering

Morphological levelings is a powerful class of self-dual morphological filters which recently have been proposed as an effective tool for image scale space simplification and segmentation (Meyer and Maragos, 2000; Meyer 2004; Karantzalos et al., 2007).

Considering that a light region (resp. dark region) is marked by a regional maximum (resp. a regional minimum), one should look for connected operators which do not create any new extremum and which do not exchange a maximum of a minimum (and conversely). Being able to compare the values of "neighboring pixels" one can define levelings as a subclass of connected operators that preserve the grey-level order. Levelings are transformations $\Lambda(f,g)$ and in mathematical terms, based on a lattice framework, an image g is a leveling of the image f if and only if for all neighboring points in space (all neighbor pixels $\forall(p,q)$) the following equation holds:

$$g_p > g_q \Rightarrow \quad f_p > g_p \text{ and } g_q \geq f_q$$

Levelings are created when are associated to an arbitrary family of marker functions. These multiscale markers can be obtained from sampling a Gaussian scale-space. Let there be an original image $f(p,q)$ and a levelling Λ. Assuming that one can produce markers $h_i(p,q)$, $i = 1,2,3,...,$ associated with an increasing scale parameter i and calculate the leveling $\Lambda(h_i, f)$ of image f based on these markers, a multiscale representation can be produced:

The implemented, here, scale space representation is employing anisotropic diffusion filtering defined by a geometry-driven diffusion (Alvarez et al., 1992; Karantzalos et al., 2007). The markers which control the levelling computation have been already smoothed through an anisotropic manner. To this end, resulted levelings were dominated by nicely enhanced and smoothed images in which edges and abrupt intensity changes have been respected. With such a reference image the multiscale markers obtained from sampling its Gaussian scale-space, did not start blurring the original image but they started from blurring the ADF output.

2.2 Multivariate Alteration Detection (MAD)

The Multivariate Alteration Detection change detection approach (Nielsen, 1994) is an orthogonal transformation based on canonical correlation analysis between two groups of variables in order to find their linear combinations that give the maximum multivariate differences. We assume that these groups of variables are two multispectral images, with *k* number of bands, which depict the same area and they were acquired at different dates, t_1 and t_2. If the images are represented at a given pixel by random vectors $X=[X_1 \cdots X_k]^T$ and $Y=[Y_1 \cdots Y_k]^T$, which are assumed to be multivariate normally distributed ($E\{X\}=E\{Y\}=0$), then the simple difference D between the images is defined as $D= a^T X- b^T Y$. The a^T and b^T are a set of coefficients, in order to describe in a more flexible way the linear combinations of X and Y: $a^T X=a_1 X_1 + \cdots + a_k X_k$ and $b^T Y=b_1 Y_1 + \cdots + b_k Y_k$. To define the transformation coefficients vectors a^T and b^T, we maximize the $\mathrm{Var}\left\{a^T X - b^T Y\right\}$, subject to the restriction that $\mathrm{Var}\left\{a^T X\right\} = \mathrm{Var}\left\{b^T Y\right\} = 1$. In that way, the determination of difference between two linear combinations with maximum variance corresponds to linear combinations with minimum correlation (positive). In general the transformation coefficients vectors a^T and b^T are defined by a standard canonical correlation analysis. In a few words, the vectors a^T and b^T can be defined using the generalized eigenvalue problem. If *k* the number of bands, the transformation calculates *k* eigenvalues, *k* pairs of eigenvectors and *k* uncorrelated MAD components. The MAD components are the difference images of the corresponding canonical variates.

2.3 Decision thresholds for MAD components

To exploit the change information of the MAD components, it is required to distinguish the change from no-change pixels. The MAD variates follow approximately the normal distribution and tend to cluster around zero; they are also uncorrelated with each other, so the decision thresholds could be determined through standard deviation σ. The threshold value is set separately for each MAD component by considering that the intensity values that are within $\pm 2\sigma$ of zero are corresponding to no-change pixels (Canty, 2007).
In this study, the decision thresholds were defined automatically similarly as in Canty (2007). The methodology is based on the consideration that a MAD component can be represented by a simple Gaussian mixture model for a random variable M. The probability density function of M can be formed by combining normal density components of the classes no change (NC), positive change (C+) and negative change (C−):

$$p(m) = p(m \mid NC)p(NC) + p(m \mid C-)p(C-) + p(m \mid C+)p(C+)$$

The expectation maximization (EM) algorithm is then used to calculate the parameters of the mixture model. The EM algorithm assigns posterior probabilities to each component density with respect to each observation. The upper and the lower threshold for each component can be determined as soon as the model parameters converge.

2.4 Object-oriented classification scheme

The MAD transformation is an effective approach to indicate the changed areas, but, similar to other statistical change detection methods, they do not identify the exact type of change automatically. The implementation of unsupervised (Canty, 2007) or supervised (Niemeyer et al., 2007; Nussbaum and Menz, 2008) classification methods on output images is essential to label the type of changes. In this study an object-oriented classification approach is proposed towards the identification of building alterations. The general concept was an initial rough classification of changes as they were indicated in MAD components and then the exact classification of newly built structures.

The classification of the MAD components in "pixel level" was the first process of the classification methodology. The chessboard segmentation of the images, by setting the object size equal to a pixel, enabled the use of the thresholds that were automatically calculated by EM algorithm. Two change classes were defined for each MAD component, one class for the decreased grey values (MAD-) and another for the increased ones (MAD+). The visual interpretation of MAD images facilitated the association of MAD classes with the corresponding changes of land cover types. The alterations of interest were those from vegetation, bare soil and erected structures to buildings. The alterations from vegetation or bare soil to roads were not studied, so as to simplify the change detection problem. Nevertheless, the variety of roofs in the study area required different types and description of classes (features, functions and thresholds), that increased the complexity of the classification scheme. Various segmentation levels were created to assist the handling of each type of land cover change. A rule base classification scheme was finally defined and it was adjusted towards the classification of changes to tiled, bright and dark roofs.

3. EXPERIMENTAL RESULTS AND EVALUATION

3.1 Application on the original data

Firstly, the methodology was applied directly on the original dataset, i.e two pan-sharpened Quickbird orthoimages, with spatial resolution of 0.6m, acquired in July 2003 and July 2007. The images depicted the urban area of Pilea in Thessaloniki, Greece, with a size of 648*583 pixels. The transitions to tiled roofs were the first process of classification scheme, since they were concerned the majority of buildings. After the implementation of MAD transformation, the thresholds for the MAD images were defined automatically by EM algorithm and the change/no-change areas were identified. Towards the semantic definition of change information, a further processing of MAD images was proposed through an object oriented classification scheme. The interpretation of MAD images demonstrated that MAD4, specifically the class MAD4+, represented the alterations to tiled roofs. The previous class of this type of building objects could have been vegetation, bare soil and erected buildings. It was essential to take into consideration the initial state (image of 2003) of the objects, in order to define the rule set properly. Therefore the following fuzzy rules (DTR, Detection of Tiled Roofs) were set for the accurate delineation of this type of buildings:

- DTR1: If the Relative Area of sub objects MAD4+ was high, then it was probably a new structure with tiled roof. To confirm that these objects were actually buildings, the following rules were set to the certain object domain.
- DTR2: If the value of Mean Red 2007 was high and Mean Blue 2007 was low, then the possibility for an object to be a new building with tiled roof was even higher.
- DTR2a: If the value of Mean Red 2003 of this object was also high and the value of NDVI 2003 was low then this object was probably a building with tiled roof in image of 2003 and it was incorrectly detected as change.
-DTR2b: If the value of Mean Blue 2003 of an object was high and the value of MAD4 was within a certain threshold then this object was probably a building under construction in image of 2003 that altered to a building with tiled roof in 2007.

The concept of the rule set structure was to define initially the changes to tiled roofs as indicated in MAD image (DTR1). The resulted classified objects were separated into buildings and other changed objects (DTR2). Then the description of the objects in image of 2003 improved the change detection result (DTR2a, DTR2b). Applying these rules, the misclassified objects, due to shadow or different soil moisture conditions, were excluded from the further process.

A series of logical rules were then defined so as to optimize the classification result. The shape features Area and Length/ Width were conducive to eliminate very small objects and long objects that could not be buildings. Finally the "tiled roofs" objects were considered as seed objects and they expanded through a loop process of region grown algorithm, in order to refine their shape (Fig.1). The candidate condition for the region grown algorithm was defined by the class-related feature of Relative Border to neighbour object.

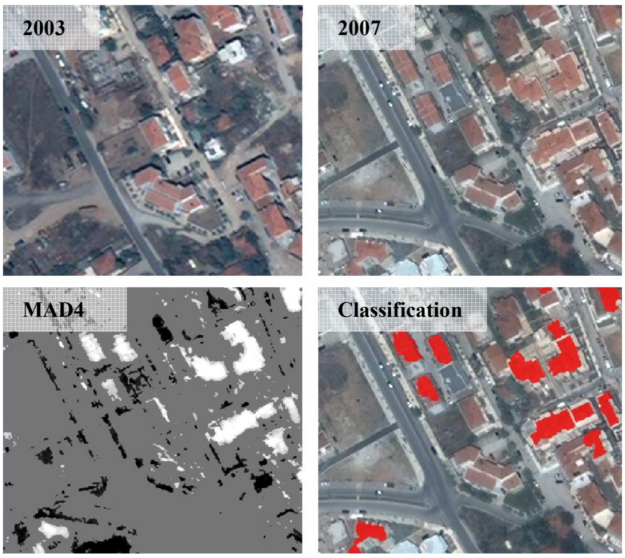


Figure 1. A subset of the original multitemporal images (top). The MAD4 component and the classification result regarding the tiled roofs (bottom).

The following procedure was the detection of bright roofs based on the information of the class MAD4-. The rule set was defined in the same sense with the classification rule set of changes to tiled roofs. In this case the alterations were from vegetation and bare soil to bright roofs. DBRs referred to Detection of Bright Roofs rule set.

-DBR1: If the Relative Area of sub objects MAD4- was high, then the object was probably a new structure with bright roof.

-DBR2: If the value of Brightness was high, then the possibility for an object to be a new building with bright roof was even higher.

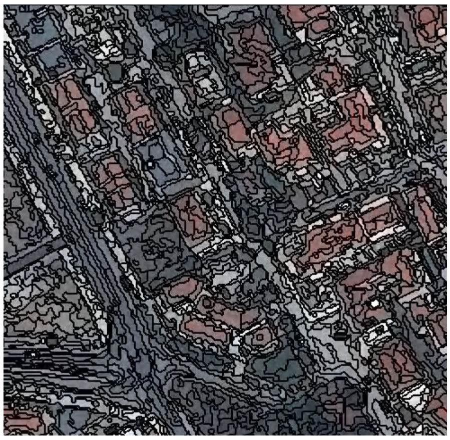
-DBR2a: If the value of Mean Blue 2003 was high then this object was probably a building in image of 2003 and it was excluded from the further process.

The definition of the shape features Area, Compactness and Length/ Width was repeated as well to enhance the shape of classified objects.

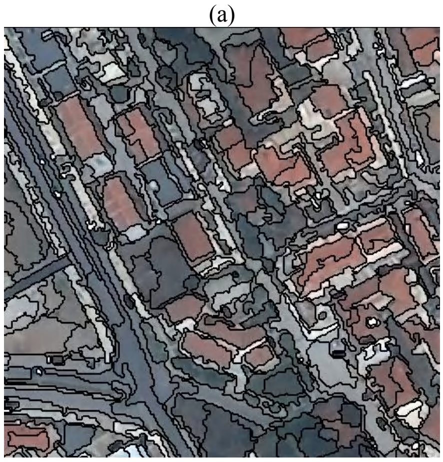
The detection of dark roofs was the final step of the classification process. The difficulty at this point was the similar spectral signatures of roads and buildings with dark roofs. Moreover, the areas of bare soil and vegetation in 2003 were altered to buildings and roads in 2007, thus these changes had similar grey values in MAD components and their distinction was a quite hard task. The rule set at this case was defined likewise to the previous ones. All the possible transitions to dark roofs were detected at first and then only the actual changes were preserved through a gradually process. The basic features of this rule set were the Mean values of MAD2, MAD3, NDVI 2007 and the value of Ratio Blue 2007. The shape features Area, Compactness, Shape Index and Length/Width were utilized to optimize the shape of detected objects and remove the image noise. The noise at this point corresponds to misclassified objects and to relatively small objects without any semantic information. The final step included the refinement of the objects boundaries by implementing the two basic morphology expressions for Opening and Closing images. Openings were used to remove small objects that cannot contain the structuring element from object boundaries and Closings to fill small holes of object boundaries. Smoother borders that approximate the buildings shape were the outcomes of both applications.

3.2 Application on the scale space images

Secondly the proposed change detection scheme was applied on simplified images. After a trial and error investigation the scale space representation of the original data were computed up to a coarse scale of a scale parameter 1000. The MAD transformation was then applied on the filtered images. The scale parameter of the multiresolution segmentation was the same with the one of the original data, so as to produce comparable results. The differences in the shape and size of the resulted objects were considerable, with the borders of the buildings in the filtered images to be delineated more specifically (Fig.2). What was also remarkable was the number of resulted objects in two case studies. The number of segmented objects of filtered image was approximately the 1/5 of the objects of the original data, a fact that facilitated the treatment of the objects.



(a)



(b)

Figure 2. The multi-resolution segmentation with a scale 20 computed on the (a) original data (11.351 objects) and (b) the scale space images (2.254 objects)

The main concept of the classification scheme was similar to the one defined for the original data. The changes were initially classified as they were indicated in MAD components and then the classification result was refined (Fig.3). The fuzzy rule set was in general the same with the “original” one, as it was described in 3.3 by DTRs, DBRs, etc. Nevertheless, the tuning of the threshold was essential, because the pixel values of the input data were different in two case studies. The most significant difference between the two rule sets was the omission of the rules for the shape optimization of classified objects. Thus, the classification scheme for scale-space images was easier to be applied, since it was more simplified.

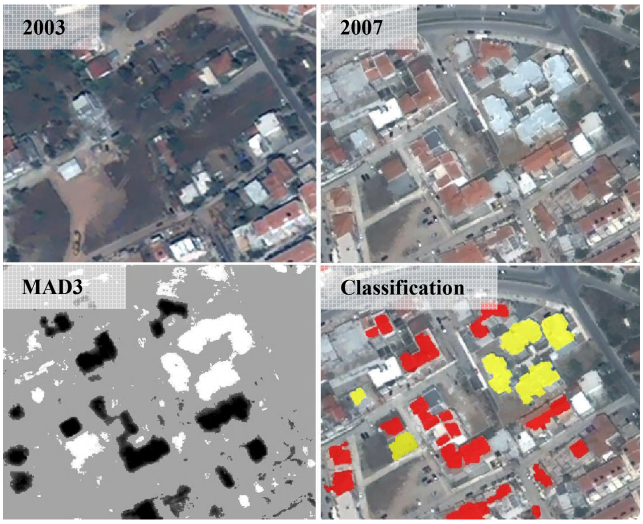


Figure 3. A subset of the scale-space multitemporal images (top). The MAD3 component and the classification result indicating the land cover changes (bottom).

3.3 Evaluation

The evaluation of change detection methodology was accomplished using ancillary ground truth data. Ground truth information included approximately 80 buildings that resulted from the visual interpretation and manual digitizing of Quickbird image. The manually delineated buildings (reference data) were used for the pixel-by-pixel comparison with the extracted classified objects. The evaluation of change detection result was performed using evaluation measures (completeness, correctness, quality) widely applied on building identification (Jin et al., 2005; Champion et al., 2009b; Karantzalos and Paragios, 2009).

The evaluation results in the case of original data demonstrated that the majority of changed buildings were fully or partly detected with correctness at approximately 86% (Fig.4). Six of the reference buildings were not identified at all and three buildings were classified as changed buildings incorrectly. The other false alarms were some courtyards adjacent to buildings. They were real changes, but their segregation from buildings was a difficult task because of the similar spectral and geometric attributes. Nevertheless, the major difficulty was the delineation of the exact shape of the buildings, since the images were acquired at off-nadir look angle. For this reason, not only the roofs, but also a part of building side was recorded and the correct position and shape of the buildings was difficult to be defined. The problem emerged in both reference data and produced classified images. The most of the omitted pixels corresponded to this part of buildings. The completeness was at 68% and the overall quality percentage was approximately 61%.

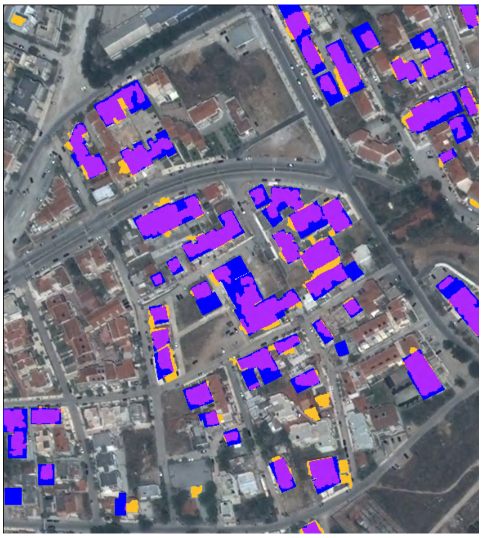


Figure 4. The purple pixels referred to the classified buildings of the original image data, the yellow pixels indicated the false alarms (False Positive: 5369pixels) and the blue pixels indicated the undetected pixels (False Negative: 16075pixels).

The same quality measures were evaluated for the classification result of scale-space images (Fig.5). The correctness of the change detection was at approximately 88% with completeness at 72%. Although, the shape of the buildings was defined more suitably in this case, there were also pixels of buildings side that were not detected at all.

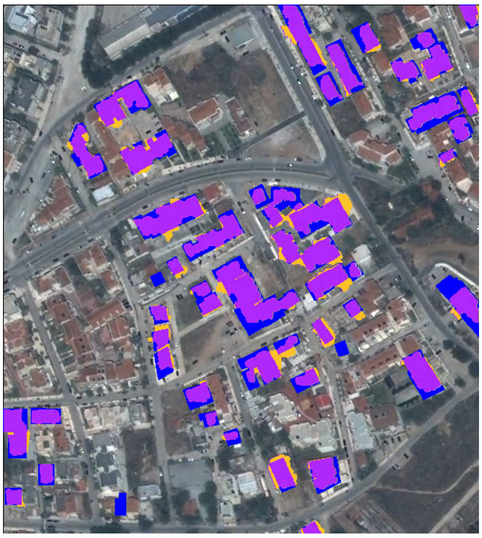


Figure 5. The purple pixels referred to the classified buildings of the filtered image data, the yellow pixels indicated the false alarms (FalsePositive: 4744pixels) and the blue pixels indicated the undetected pixels (FalseNegative: 13678pixels).

Quantitative measures	**Original Dataset**	**Scale Space Filtering**
Completeness	68%	72%
Correctness	86%	88%
Quality	61%	66%

Table 1. Quantitative Evaluation.

A visual interpretation of the three omitted buildings indicated that they were either an extension of an existing building or small-sized buildings (Fig. 5). Therefore, it was difficult to detect them because of their similar spectral response to neighbouring pixels. Moreover, there was no incorrectly detected building and the false alarms were only pixels of courtyards adjacent to buildings. The overall quality of the proposed methodology was about 66%.

4. DISCUSSION

The experimental results are indicating the potentials of the developed scheme despite the important difficulties towards the automated monitoring of the urban environment. The spectral and spatial variety of urban features hampered the exact detection of land cover alterations. Towards the handling of urban complexity, it was essential to combine spectral, geometric and topological information under an object-oriented classification framework. Morphological scale space filtering was embedded in the processing scheme and improved the quality of object extraction. The elegantly simplified images provided meaningful objects that facilitated the classification procedure, since the rules that were set in the case of original data for smoothing the object shape were excluded in this case. Therefore, the object-oriented scheme with the scale space filtering was more simple, robust and fast. In general, less number of rules requires less time for tuning of thresholds, a fact that affects not only the time of system implementation but also the system transferability.

Despite the improved change detection results with the simplified data, the variety of buildings shape and the heterogeneity of roof types limited the effectiveness of the proposed methodology. The evaluation results demonstrated that most of the omitted pixels were parts of the side of the buildings. Since the images were collected at approximately 20º off-nadir angle, they recorded information not only from the top, but also from the side of the buildings. Therefore the accurate position and the exact shape of the objects were difficult to be defined. This problem emerged in the manual digitization of reference data and thus, during the evaluation of the developed methodology. In the case of datasets with an acquisition of 0º off-nadir angle, quantitative results are expected to be enhanced, since due to the delineation of the roofs the texture is expected to be simpler.

5. CONCLUSIONS

An approach towards the land cover change detection, focusing mainly on buildings, was developed aiming at the automated monitoring of the urban environment. Despite the lack of ancillary data (LIDAR data, existing geodatabases, etc), the evaluation results demonstrated the potentials of the proposed methodology. The elegantly simplified images from the morphological scale space filtering provided a more compact and reliable source, in order to generate image objects in various scales. The MAD transformation was able to detect the majority of urban changes with an automated way. An object-based approach for labelling the changes allowed the exploitation of spectral, shape and contextual information of urban features for an effective classification result. Moreover, the simplified data contributed to a fine segmentation and resulted to a more robust, simple and fast rule set structure. Nevertheless, ancillary data would support the further improvement of the proposed change detection system. Additional information of existing geodatabases for the buildings shape and position would be essential for the training of the system. The height information also of LIDAR data would facilitate the discrimination of buildings from other urban objects with similar spectral and shape characteristics.

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